Bidder and Target Size Effects in M&A Are Not Driven by Overconfidence or Agency Problems*

Christoph Schneider
University of Münster
christoph.schneider@wiwi.uni-muenster.de

Oliver Spalt
University of Mannheim
spalt@uni-mannheim.de

January 25, 2022

Abstract

The impact of size variables on bidder announcement returns can be decomposed into two effects, the "size as proxy effect" which was the focus of the prior M&A literature, and a "scaling effect" which magnifies per-dollar value created in a given deal. Using data of US takeovers from 1981 to 2014, we document that small bidders make better acquisitions than large bidders when they acquire non-public firms, but worse acquisitions when they acquire public firms, which is inconsistent with size as proxy explanations (e.g., size proxying for overconfidence of a firm's managers or agency problems). The pattern is consistent with scaling, because value created for bidders is on average negative for public target deals, but positive for non-public target deals. Scaling creates additional predictions for target size, relative size, and international M&A deals we show are borne out by the data.

Keywords: Mergers and Acquisitions, Size Effects, Scaling.
JEL Classification: G34, G14

*We would like to thank Kenneth Ahern, Nihat Aktas, Sugato Bhattacharyya, Joost Driessen, Gerard Hoberg, Matthias Kahl, Ron Masulis, Ernst Maug, Han Kim, Gordon Phillips, Per Stromberg, Toni Whited, Dong Yan, Ke Yang, and seminar participants at Australian National University, University of Cologne, University of Frankfurt, Frankfurt School of Finance & Management, Humboldt University of Berlin, University of Mannheim, University of Michigan, Monash University, University of Münster, University Paris Dauphine, University of St. Gallen, University of Technology Sydney, Tilburg University, the 2016 DGF conference, the 2016 Stockholm School of Economics Finance Symposium, the 2016 Western Finance Association Conference, and the 2018 SFS Cavalcade Asia-Pacific for valuable comments and suggestions. We are responsible for any remaining errors or omissions. A previous version of this paper was titled: "Why does size matter so much for bidder announcement returns?"

A central question in the M&A literature is which transactions generate shareholder value for the acquiring firm (the "bidder"), usually measured by bidder announcement returns from short-term event studies. The size of the bidder consistently emerges as a key variable explaining variation in bidder announcement returns.[1] For example, in a standard data set of 27,000 domestic US takeovers from SDC over the period from 1981 to 2014 used in this paper, the spread in average three-day bidder announcement returns, between the top and the bottom bidder size quintiles without additional controls is 3% ($t = 16.7$). Target size is similarly important. With little dispute about the empirical power of size variables to explain variation in bidder announcement returns, the central economic question is: *why* does size matter for bidder announcement returns?[2]

The predominant approach in the recent M&A literature is to interpret size as a proxy variable for some underlying economic driver. Existing proxy explanations include size proxying for managerial skill, managerial overconfidence, the presence of agency problems, overvaluation, availability of growth opportunities, cash constraints, effectiveness of merger arbitrage, information available about a firm, and a firm's competitive environment. Despite this bewilderingly long list, and unanswered questions about which explanation should be preferred and in which context, there seems to be a near consensus in the literature that size is best interpreted as a proxy for some underlying value driver that impacts value creation for bidders.

Our paper argues that this emphasis on bidder size as a proxy variable is misplaced. It has three parts. In the first part of the paper, we revisit the facts in the data, using the data set mentioned above. We start by splitting the data by public and non-public targets. Splitting the sample in that way is motivated by empirical relevance: the non-public target subsample represents more than 85% of all observations, while the public target subsample represents about 64% of total dollars spent on acquisitions. It is also motivated by relevance for the literature: almost one half of published studies restrict themselves to public targets, while the other half uses both public and non-public targets.

The analysis documents strong reversal patterns (i.e., flipping signs) in the data across the subsamples, summarized in Table 1: (i) for non-public target deals, holding constant the size of the

[1] For example, in a survey article on the M&A literature, Betton, Eckbo, and Thorburn (2008) call bidder size one of *"the two key drivers"* of bidder announcement returns.

[2] While our empirical work below will look at both, bidder and target size, we will use the term "size" in the following when the discussion is equally relevant for both bidder and target size, or when the context is such that no confusion can occur.

target, larger bidders are associated with lower bidder returns, and, holding constant the size of the bidder, larger targets are associated with higher bidder returns, and, (ii) for public target deals, *all signs reverse*. These reversal patterns are very robust. They show up in sorts and regressions, and they are not driven by particular industries and time periods. We argue that reversal patterns shown in Table 1 is a main regularity to explain. They represent a simple but sharp test on existing proxy explanations for size effects in the recent M&A literature.

Table 1: Key Facts in the Data

This table shows the sign on bidder and target size variables, respectively, when bidder announcement returns are regressed on these size variables (as well as controls) in the sample of domestic US takeovers we use in this paper.

Interpretation: This table presents the reversal pattern central to this paper. Within public and private target subsamples, bidder and target size variables have opposite signs. Across subsamples, bidder (target) size has a positive sign in one subsample, and a negative sign in the other. This pattern is hard to explain by existing size as proxy explanations, but consistent with the scaling explanation advocated in this paper.

Subsample:	Sign when regressing bidder announcement returns on controls and ...	
	Bidder Size	Target Size
Private Targets:	−	+
Public Targets:	+	−

In the second part of the paper, we show that the leading explanations for size effects in the recent M&A literature do not predict signs to flip across the subsamples. For example, influential prior work by Moeller, Schlingemann, and Stulz (2004) suggests the bidder size effect may be driven by managerial overconfidence, under the assumption that managers in larger firms are more overconfident, and that more overconfident managers are more likely to make bad deals. But, under the overconfidence hypothesis, smaller firms should also make better acquisitions when they acquire a *public* target. Because we find precisely the opposite, the reversal test casts doubt on the hypothesis that size matters because it proxies for overconfidence. Similar arguments apply to virtually all other size as proxy explanations proposed in the recent literature.[3]

In the third part of the paper, we argue that the previous literature is trying to explain patterns that are easier to explain by a simple scaling model. We start by showing analytically that the

[3] To avoid misunderstandings: we do not argue, and our results in this paper do not imply that managerial overconfidence (or other potential value drivers like agency concerns) would not matter in the M&A context in general.

impact of size variables on bidder announcement returns can be decomposed into two effects, the "size as proxy effect" which was the focus of the prior literature, and a "scaling effect".

Scaling refers to the property that bidder and target size (and, therefore, relative size) magnify a given per-dollar gain or loss in a given takeover. The intuition is simple. A bidder who loses n cents on every dollar invested will, all else equal, lose more if it invests more. Hence, for a given size of the bidder, a larger target implies a larger percentage decrease in the value of the bidder if n is negative. If we fix target size instead, and therefore the dollar loss from the transaction, the percentage drop in the value of the bidder will be smaller, the larger the bidder. For a bidder that gains n cents on every dollar invested, analogous reasoning implies that larger targets and smaller bidders lead to larger percentage changes in bidder value. While the scaling intuition is not new and goes back at least to Asquith, Bruner, and Mullins (1983), the more recent literature on the impact of size on bidder returns has largely abandoned it in favor of size as proxy explanations.

We show that scaling can explain both, (i) the opposing signs on bidder and target size coefficients within public and non-public deal subsamples, respectively, and (ii) the sign-flip of target and bidder size coefficients across the public and non-public deal subsamples, shown in Table 1. The reason is that the average deal in the public deal subsample has negative per dollar NPV, while the opposite is true for the average deal in the non-public deal subsample (we document these facts below). Once we know the sign of the per-dollar NPV, we can apply the logic from the previous paragraph to each subsample and show that scaling predicts the reversal pattern. By contrast, and as illustrated above, size as proxy explanations do not predict reversals.

Scaling is a good model in a Friedman (1953) sense: it is parsimonious and still explains the first-order effects in the data that are at odds with explanations in the existing literature. It also makes additional testable predictions. In particular, a sharp additional prediction of the scaling framework is that, for a given size variable, the sign reversals should also occur *within* public and non-public deal samples and not just across these samples. We test this prediction using quantile regressions and find results consistent with the scaling model.

The quantile regressions also confirm another prediction of the scaling model: the sign of the derivative of bidder announcement returns with respect to bidder and target size, respectively, should flip at the same percentile of the bidder return distribution. This simultaneous sign-flip, which is not predicted by any size as proxy explanation we are aware of, is a strong piece of evidence supporting the scaling view. The finding also suggests that bidder and target size are not distinct variables that need separate theories linking them to bidder returns, which contrasts markedly with the approach taken in much of the existing literature. From an identification standpoint, the within-subsample reversals we document raise the bar for alternative interpretations of our findings considerably. They also show it is unlikely that our results obtain because of omitted variables, or because non-public and public target deals are selected subsamples.

The results of our paper have several important implications for the M&A literature. First, to understand why size matters for bidder announcement returns, bidder and target size are best interpreted as scaling variables, not as proxies for some underlying value drivers. Second, bidder and target size are not distinct variables that need separate theories linking them to bidder returns. Scaling provides a unifying framework. Third, a prominent stylized fact in the literature, which continues to influence both empirical and theoretical studies on takeovers, is that *"smaller bidders make better acquisitions"* (e.g., Moeller, Schlingemann, and Stulz (2004), Betton, Eckbo, and Thorburn (2008), Gorton, Kahl, and Rosen (2009)). The reversal evidence shows that *"smaller bidders make better acquisitions"* is a reasonable starting point for empirical or theoretical work only in some specific contexts, but, because central parts of the data show the precise opposite pattern, it should not be viewed as a stylized fact about takeovers in general. Interpreted more broadly, our paper illustrates the dangers of too uncritically accepting explanations for economic phenomena based on very indirect proxies.

In terms of methodology, our paper is simple. We do not exploit a natural experiment or other exogenous shock to our variables of interest. Our evidence is based on "old-fashioned" marginal correlations by necessity. This approach follows the literature, because marginal correlations are so far the only viable evidence on this question of great importance to the M&A literature.

1 Data

The data we use are standard in the literature on takeovers. Our initial sample consists of all takeover bids of public US bidders for public and non-public US targets in the Thomson Reuters SDC database from January 1, 1981 to December 31, 2014. We require that the bidder owns less than 15% of the target before the announcement and more than 80% after the transaction is completed. We exclude deals with missing deal value, penny stocks, repurchases, recapitalizations, rumored, and target solicited deals. Following Moeller, Schlingemann, and Stulz (2004), we eliminate deals with below 1 million US$ deal value and deals with relative size (deal value over bidder market capitalization) smaller than 1%. We obtain stock price data from CRSP and balance sheet data from Compustat.

We calculate bidder and target cumulative abnormal returns over a three day window around the announcement. Abnormal returns are determined relative to a market model estimated over days -280 to -31.

Bidder size is measured by market capitalization, defined as price (CRSP: PRC) times shares outstanding (CRSP: SHROUT), at the last fiscal year end before the announcement. Target size is measured for public and non-public targets by deal value (as reported in SDC), but we have verified that our main results also obtain when we replace deal value by market capitalization before the announcement (which is available only for public targets). All variables denoted in US$ are adjusted for inflation and expressed in 2014 constant US$.

We control for a set of standard variables in our regressions (e.g., Baker, Pan, and Wurgler (2012), Moeller, Schlingemann, and Stulz (2004)). We control for the return on assets, defined as EBITDA (Compustat: EBITDA) over total assets (Compustat: AT), and the book to market ratio, defined as book equity divided by market capitalization, where book equity is total shareholders' equity (Compustat: SEQ) plus deferred taxes and investment tax credit (Compustat: TXDITC) minus the redemption value of preferred stock (Compustat: PSRKRV). All these variables are based on the bidder's last fiscal year end before the announcement. We control for a set of deal characteristics obtained from from SDC, including dummy variables indicating payment through stock only or cash only, tender offers, hostile takeovers, conglomerate mergers (mergers in which the bidder is in a different 2-digit SIC code industry than the target), and competed deals (with more than one bidder). We also include a dummy variable indicating new economy firms (classified by SIC codes 3570 to 3579, 3661, 3674, 5045, 5961, or 7370 to 7379), and the number of transactions in the same 2-digit SIC code industry and year, to control for periods of heightened M&A activity in all our regressions. We include additional fixed effects for industry, year, and industry $\times$ year in our regressions where appropriate. Table 2 presents summary statistics (we provide additional details on the sample in the Internet Appendix A.2, Table A-1 and A-2).

As a basis for distilling common practices related to, and interpretations of, size variables in the literature we conduct a scan of the M&A literature. Specifically, we try to identify all M&A papers published from 2000 to 2017 in the *Journal of Finance* (JF), the *Journal of Financial Economics* (JFE), *Management Science* (MS), and the *Review of Financial Studies* (RFS). We restrict the search to these journals and this period to keep the data collection manageable. To the extent that papers published in these journals are, on average, of a higher quality than other papers, focusing on these journals allows us to gauge how some of the best work in the M&A literature deals with size controls and size as proxy explanations. We list the 238 papers we analyze in the Internet Appendix A.3, and we comment on the key findings in the text. 88 papers present a regression with short-term bidder announcement returns as a dependent variable, which is the focus of our paper.

Some of our tests analyze a sample of European takeovers. We obtain data on all mergers and acquisitions in the Thomson Reuters SDC database, performed by bidder firms from current EU countries as well as Iceland, Lichtenstein, Norway, Switzerland, and the UK announced between January 1, 1980 and December 31, 2017. We obtain additional firm-level data from Datastream. We otherwise use the same sample selection criteria as for our main US sample.

2 Facts in the Data: The Bidder Return-Firm Size Relation

In this section we present the relation between bidder size, target size, and bidder announcement returns in the data. A feature of our empirical design is that we analyze the subsample of public targets and non-public targets, separately. We document differences in the size-bidder return patterns across the subsamples which we later show are informative for understanding which explanations capture the role size plays for bidder announcement returns. While we split the sample into public target and non-public subsamples in this section, we emphasize and show below that our paper is fundamentally *not* a paper about public vs. private targets. Public and non-public subsamples are simply laboratories that are well suited for showing our main effects in important parts of the M&A data.

2.1 Non-Public Targets

We start by describing the data for non-public targets. Because non-public targets are so plentiful (86% of all observations in our full data set are from non-public targets), results for the full sample of public plus non-public targets are qualitatively similar to the non-public target deal subsample. We present sorting results for non-public targets only and omit the full sample results for brevity. Panel A of Table 3 sorts bidder cumulative announcement returns (ACARs) into five bidder size groups. Bidder returns decline monotonically when going from the smallest to the largest bidders, which is the bidder size effect documented by Moeller, Schlingemann, and Stulz (2004). The difference between smallest and largest bidder quintile is 2.5 percentage points ($t = 12.4$) and therefore economically substantial. Panel B shows there is a weaker, but still significant tendency of ACARs to increase in target size.

An issue with univariate sorting is the strong correlation between bidder and target size in the data ($\rho = 0.71$ in logs), which is also apparent from the size numbers across quintiles shown in Panels A and B. Larger bidders take over larger targets that are at the same time relatively smaller. The correlation between bidder and relative size (all in logs) is -0.4. Sorting by one size variable means we are also, implicitly, sorting on the other one. To get a clearer picture of the incremental impact of target and bidder size, Panels C and D summarize results from double-sorts. In Panel C, we first sort the sample into target size quintiles, and then, within each quintile, we sort on bidder size. Panel C then presents for each bidder size quintile the weighted average across all associated target size quintiles.[4] The bidder size effect, i.e. "smaller bidders make better deals," gets even stronger in this case. Panel D repeats the exercise when reversing the order of sorting. At 2.8 percentage points ($t = 13.1$), the difference between top and bottom target size quintile is highly significant both statistically and economically. Hence, the correlation between bidder and target size in the univariate sorts masked part of the substantial impact target size has on bidder returns.

The size averages across groups in Panels C and D show that the double-sort does not perfectly remove the correlation between target and bidder size. We therefore, in a next test, regress ACAR on a full set of bidder size quintile dummies (without a constant) and demeaned target size. Figure 1, Panel (a) shows that removing the correlation between bidder and target size by controlling

[4] The complete 5×5 matrix is reported in the Internet Appendix A.2, Table A-3.

for target size further increases the effect of bidder size. ACARs for deals by large acquirers (top quintile) have 4 percentage points lower announcement returns than deals done by small bidders. Panel (b) shows that the pattern for target size quintiles is the mirror image of the patterns for bidder size quintile in Panel (a).

Table 4, Panel A, presents results from regressions of ACARs on the logs of bidder and target size, as well as a set of standard variables used in the literature (see Section 1). Specifications (1) and (2) present the full sample results (non-public and public targets), and specifications (3) and (4) show results for the non-public subsample. Across all specifications (1) to (4) there is a strong negative association between bidder size and bidder returns, and specifications (2) and (4) show there is also a strong positive association between target size and bidder returns. The results are thus consistent with our sorting evidence and show that the size-bidder return patterns in the sorts are not induced by deal characteristics, firm characteristics, or industry characteristics.

The regressions in Panel A include year and bidder industry fixed effects and therefore remove potentially confounding time-invariant heterogeneity along those dimensions. One specific concern could be that mergers cluster by industry and year, and that our patterns are driven by time-varying industry-level factors, which our year and industry fixed effects are not sufficiently controlling for. To address this, we repeat the tests from Table 4, Panel A, but now include bidder industry $\times$ year fixed effects and target industry $\times$ year fixed effects. Specifications (1) to (4) of Table 4, Panel B, show that our results are effectively unchanged.

In sum, there are three important takeaways from this section. First, bidder and target size are highly correlated. To accurately measure the incremental impact of one size variable, one needs to control for the other. Second, once this correlation is taken into account, the size return patterns for bidder size are the mirror-image of the patterns for target size. Third, the stylized fact that smaller bidders make better acquisitions in term of ACAR is a robust feature of this subspace of the merger universe.

2.2 Public Targets

We now turn to the subset of deals with public targets. Panel B of Table 2 shows that out of a total of about 27,000 deals in our sample, less than 4,000 involve public targets. Hence, the "average deal" is one involving a non-public target. However, public deals represent about 64% of the dollars spent on takeovers in our sample, so the "average dollar" is spent on a public target. The reason is that public target deals are on average more than ten times larger than non-public target deals. As shown in Table A-9 in the Internet Appendix A.3, 41% of the papers, we survey, regress bidder announcement returns on explanatory variables focus exclusively on public targets. The subset of public deals is therefore both economically and academically important.

Table 5 repeats the sorting exercise from Table 3, but this time with public deals. In the simple sort by bidder size, in Panel A, the bidder size effect we previously found for non-public deals is also present for public firms, albeit weaker. However, Panel C shows that once we sort by bidder size within target size quintile, and therefore remove some of the confounding positive correlation with target size, the sign on bidder size flips from negative to positive. Now, larger bidders make better acquisitions, with a significant difference of 0.8 percentage points between the extreme quintiles ($t = 2.0$). This finding is remarkable, because it reveals a stark difference between the non-public and public target deal subsamples: bidder size affects bidder returns *significantly, but with opposite sign.*

A set of more refined tests strengthen this conclusion. To better measure the true incremental effect of bidder size, we regress ACAR on a full set of bidder size quintile dummies (without a constant) and demeaned target size. Figure 1, Panel (c) presents results. While the pattern is not perfectly monotonic, it is obvious from the data that *larger* bidders make better acquisitions for public targets, while the reverse is true for non-public targets (Panel (a)).

Table 4, Panel A, specifications (5) and (6) present results from regressions which control for firm, deal, industry, and year characteristics. Specification (5) shows that, without controlling for target size the coefficient on bidder size is negative for the public target deal subsample, consistent with the results for the full sample and non-public deals (specifications (1) and (3)). However, once we introduce the control for target size in specification (6), the coefficient reverses and becomes statistically significant with the opposite sign. This again highlights that controlling for target size is critically important for determining the true incremental impact of bidder size on bidder returns. Nevertheless, only 30% of the 88 papers in the JF, the JFE, the RFS, and MS, which run similar regressions since the year 2000 are including a control for target size (see Table A-9).

Specifications (5) and (6) in Panel B of Table 4 address the potential concern that unobserved time-varying heterogeneity on the industry level is inducing our results. In these specifications we include bidder industry × year fixed effects and target industry × year fixed effects to control for these, potentially unobserved, sources of confounding variation. Using this more stringent approach of comparing deals in the same industry-year cell of our data almost doubles the coefficient on bidder size and increases its statistical significance substantially (T-values are now 3.9 and 3.6, respectively). The effect is economically large. For example, the results in specification (5) of Table 4, Panel B, imply that a one standard deviation increase in bidder size increases ACARs by 0.9%.

Looking at target size reveals a similarly striking difference between the non-public and public subsamples. While larger targets were associated with higher ACARs for non public targets, they are associated with smaller ACARs for public targets. These patterns show up strongly in simple sorts (Table 5, Panel B) and double-sorts (Table 5, Panel D), where large targets are associated with 2.3 ($t = 6.5$) and 1.9 ($t = 5.3$) percentage points lower ACARs, respectively. They also show up strongly in Figure 1, Panel (d), where we regress ACAR on target size quintiles while controlling for demeaned bidder size. Finally, they show up strongly in the multivariate regressions in Table 4, Panel A, specification (6), and in Panel B, specifications (5) and (6), where we control for bidder industry × year fixed effects and target industry × year fixed effects.

Tables A-4 to A-7 in the Internet Appendix A.2 present additional robustness checks. There we show that our main results obtain also when we focus on serial acquirers, when we control for a measure of CEO overconfidence due to Malmendier and Tate (2015), when we control for the time to completion of the deal, and when we control for the number of analysts following the bidder and the target.

2.3 Summary of Key Results

The key results from our look at the data are summarized succinctly in Figure 1. The figure shows strong reversal patterns (i.e., flipping signs), both within and across subsamples of public and non-public target deals, respectively.

Within subsamples, we observe that bidder returns increase in target size whenever bidder returns decrease in bidder size, and vice versa (compare Panel (a) with Panel (b), and Panel (c) with Panel (d)). *Across* subsamples, we observe that bidder and target size patterns are mirror images: while, for non-public target deals, bidder returns decrease in bidder size, bidder returns increase in bidder size in the public target deal subsample (compare Panel (a) with Panel (c)). And while, for non-public target deals, bidder returns increase in target size, bidder returns decrease in target size in the public target deal subsample (compare Panel (b) with Panel (d)). As we have shown above, these are important regularities in the data.

3 Implications

3.1 Do Small Bidders Make Better Acquisitions?

The above results speak to an influential idea in the literature: "small bidders make better acquisitions," which is often associated with the study of Moeller, Schlingemann, and Stulz (2004). Survey papers like Betton, Eckbo, and Thorburn (2008) echo that smaller bidder make better acquisitions, and theory papers like Gorton, Kahl, and Rosen (2009) start with the premise that "smaller bidders make better acquisitions" is a fact that a theoretical model should match.

In contrast to that idea, our findings in the previous section document that "small bidders make better acquisitions" is a much less general fact in the data than commonly thought. In fact, *larger bidders make better acquisitions* for public target deals, once we move beyond simple univariate sorts and control for target size.[5]

3.2 Size as Proxy Explanations

All previous results are in line with the widespread belief in the literature that size matters for bidder announcement returns. The central question, then, is: *why* does size matter for bidder announcement returns?

For starters, note that, among the 88 top journal papers in the M&A literature we survey in Table A-9 in the Internet Appendix A.3, size is almost exclusively interpreted as a proxy for some underlying value driver (we comment on some of them below, and present additional examples in Table A-10). There are at least two potential issues with proxy explanations in this context. First, firm size may plausibly correlate with many things, which makes it challenging to differentiate

[5] Alexandridis, Fuller, Terhaar, and Travlos (2013) also find that the bidder size effect no longer obtains for public targets when target size is controlled for. As they do not analyze non-public deals, their study leaves open the question whether the bidder size effect remains present for deals other than public. Our evidence shows this is indeed the case. To understand size-related patterns, the authors propose a size as proxy mechanism we show is inconsistent with the reversal results (see Section 3.2).

between alternative proxy explanations. Second, the sign on the relationship between size and a proposed value driver is often debatable. To give just one example, the quality of managerial decision-making (and therefore bidder returns), may be higher in small firms, if agency problems are less of a concern in smaller firms; alternatively, quality may be lower in smaller firms, under the assumption that well-functioning labor markets should match higher skilled managers with larger firms (e.g., Gabaix and Landier (2008)). Both issues put a limit on our understanding of why size variables correlate with value creation for bidders in M&A transactions.

We propose a way forward by using the reversals from Figure 1 as a simple but sharp test on existing size as proxy explanations. The test is powerful, because the size-bidder return relations in Figure 1 are significant with *opposite* signs across the public and non-public target subsamples and because existing size as proxy explanations have a hard time predicting flipping signs across subsamples. Let us illustrate this idea by analyzing three prominent recent explanations in the literature, two on bidder size and one on target size effects.

Perhaps the most widely cited explanation for bidder size effects is managerial overconfidence. According to that hypothesis, overconfident managers make worse deals on average (as in, e.g., Roll (1986)). And, because of the self-serving attribution bias, managers in large firms are hypothesized to be more overconfident on average (e.g., Moeller, Schlingemann, and Stulz (2004)). The reversals pose a challenge to the overconfidence explanation. Because managers in larger firms are more overconfident, larger bidders are predicted to make worse acquisitions, consistent with the pattern we observe for non-public targets in Panel (a) of Figure 1 (e.g., Moeller, Schlingemann, and Stulz (2004)). However, and importantly, overconfident managers in large firms are predicted to also make worse acquisitions when they acquire public targets. The fact that larger bidders make *better* acquisitions when they acquire public targets (Figure 1, Panel (c)), thus cannot be explained by managerial overconfidence unless one believes managers in large firms are more overconfident than small-firm managers when they acquire a non-public target, but less overconfident than small-firm managers when they acquire a public target. This seems implausible. We conclude that the overconfidence explanation for size effects is rejected by the reversal test.

This basic idea is widely applicable. For example, it has been suggested that bidder size may proxy for agency problems (e.g., Masulis, Wang, and Xie (2007)), and it has been suggested that target size proxies for deal complexity (e.g., Alexandridis, Fuller, Terhaar, and Travlos (2013)).

Completely analogous reasoning as in the overconfidence example suggests that the reversals are inconsistent with these proposed mechanisms. To the best of our knowledge, there is no size as proxy explanation in the recent M&A literature consistent with the sign-reversals in bidder and target size coefficients we document across public and non-public subsamples.

Let us be more specific on why we think the reversal test is useful. While, in a strict mathematical sense, finding one counterexample is sufficient to reject a statement as true, one empirical counterexample is in general not enough to reject an economic theory. What we should care about, instead, is whether a proposed economic mechanism fails to explain an economically significant part of the data. The value of the reversal test lies precisely there: the non-public and public target subsamples are both widely studied and economically important in terms of number of deals and money invested. So our contribution is not to show that a proposed explanation in the literature, like overconfidence, fails to describe some opaque corner of the data. Our contribution is to show those explanations fail to describe the core of the data.

Finally, note that while our evidence cannot rule out that some of the existing size as proxy theories are relevant (proxy explanations are not mutually exclusive with scaling), it effectively rules out that they are the main driver of the observed patterns. We argue that, by appealing to size as proxy explanations, the previous literature is trying to explain patterns that are easier to explain by a simple alternative framework (presented in the next section) in which size is not a proxy, but a scaling variable.

4 Beyond Proxies: A Simple Scaling Explanation

We start with the basic fact that the value of the bidder after the announcement of a takeover is the value of the bidder before the takeover, plus the NPV of the deal that accrues to the bidder.

$$B_{post} = B + NPV(Deal) = B + R \times T, \tag{1}$$

where B is the size of the bidder, measured as market value of equity before the announcement, B_{post} is the size of the bidder after the announcement, T is the size of the target, and $R \equiv NPV(Deal)/T$ is the per-dollar value generated (this quantity is referred to as profitability index in standard finance textbooks).[6] The bidder announcement return, which is the percentage change in bidder value due to the takeover, is therefore

$$ACAR \equiv (B_{post} - B)/B = R \times (T/B). \tag{2}$$

Conditional on the size of the target, a change in bidder size induces a change in ACAR by

$$\frac{\partial ACAR}{\partial B} = \frac{\partial R}{\partial B} \times (T/B) - \frac{R \times T}{B^2}. \tag{3}$$

Equation (3) shows that a change in bidder size affects bidder announcement returns via two channels. The first channel, captured by the first term on the right hand side of the equation, is that bidder size may affect the profitability index of the deal, i.e., per-dollar value R generated by the transaction for the bidder. The second channel, captured by the second term, is what we call a "scaling" effect: the same dollar amount of value created by a given takeover ($R \times T$) will translate into a smaller percentage change in the value of the bidder for larger bidders. For example, if a deal creates value of 100 to a bidder, this will increase the bidder's value by 10% if bidder size is 1,000, but only by 1% if bidder size is 10,000. On the other hand, if a deal creates a loss of -100 to a bidder, this will decrease the bidder's value by -10% if bidder size is 1,000, but only by -1% if bidder size is 10,000.

The basic relationship in equation (3) illustrates the problem with size as proxy explanations in the literature: those explanations emphasize the first effect, but implicitly neglect the second effect. For example, the hypothesis that managers in large firms are more overconfident and thus make worse decisions implicitly posits that $\frac{\partial R}{\partial B} < 0$, but is not related in a meaningful way to the second term in equation (3). However, once we neglect the scaling term, the sign on $\frac{\partial ACAR}{\partial B}$ is fully determined by the sign on $\frac{\partial R}{\partial B}$. To explain why bidder announcement returns decrease with bidder size for non-public targets, but increase with bidder size for public targets, any feasible size as proxy explanation would need to posit $\frac{\partial R}{\partial B} < 0$ for non-public targets, but $\frac{\partial R}{\partial B} > 0$ for public targets. Neither the overconfidence hypothesis, nor any other size as proxy explanation we are aware of would predict such a sign flip.

[6] For simplicity, and to focus on our main effect of interest, we abstract from potential variation in bargaining power between targets and bidders of various sizes, and potential revaluation effects of the bidder itself.

We suggest that, to understand the reversal patterns in the data, we should focus on the second term in equation (3). To see why, consider the polar case of a *pure scaling model*, i.e., a model in which $\frac{\partial R}{\partial B}$ in equation (3) is zero. (While this is a polar case, we show below that it approximates the actual data quite well.) In the scaling model, the sign of $\frac{\partial ACAR}{\partial B}$ is equal to the sign of $-R$. Hence, whether bidder announcement returns increase or decrease with bidder size depends on whether the NPV created in the deal for the acquirer is positive or negative. The simple numerical example above captures precisely that effect. Analogous reasoning shows that for target size, the sign on $\frac{\partial ACAR}{\partial T}$ is equal to the sign of R.

The pure scaling model thus delivers three straightforward predictions: first, the sign of the bidder announcement return is equal to the sign of the profitability index (R). Second, if $R > 0$, then, all else equal, bidder announcement returns increase in target size, and decrease in bidder size. Third, all signs flip when $R < 0$. There are additional predictions we discuss below.

If we apply the same predictions to samples of deals, rather than individual deals, the reversal patterns in the data are no longer puzzling. Specifically, for the sample of public target deals, Table 2, Panel A shows a negative average bidder announcement return of -1.4%, which implies $R < 0$ for the average deal in that sample (direct computation of $R = ACAR \times B/T$ yields $R = -8.27\%$). The scaling model then predicts bidder returns are related positively to bidder size and negatively to target size, consistent with what we have shown in Table 4, Panel A, specification (6), and in Panels (c) and (d) in Figure 1. Conversely, in the sample of non-public targets, the average ACAR is 1.4%, which implies $R > 0$ (direct computation yields $R = 6.84\%$). Hence, the model predicts a reversal in signs, compared with the public target sample, which explains the patterns in Table 4, Panel A, specifications (1) to (4), and in Panels (a) and (b) in Figure 1.

The intuition is simple. A bidder who loses n cents on every dollar invested will lose more if it invests more. Hence, for a given size of the bidder, a larger target implies a larger percentage decrease in the value of the bidder if n is negative. If we fix target size instead, and therefore the dollar loss from the transaction, the percentage drop in the value of the bidder will be smaller, the larger the bidder. For a bidder that gains n cents on every dollar invested, analogous reasoning implies that larger targets and smaller bidders lead to larger percentage changes in bidder value.

The pure scaling model was derived under the assumption that the first term in equation (3) is zero, which is the case if $\frac{\partial R}{\partial B}$ is zero. For target size it assumes $\frac{\partial R}{\partial T}$ is zero. While we would not expect this to be literally true in the actual data, we can measure R in the data to gauge whether the approximation is empirically defensible. Table 6 presents results. Across all specifications, we are never able to reject the null that the profitability index R is the same across size groups. Comparing coefficients across size groups indicates that differences across groups are overall modest. These conclusions hold up also when we use 10 size bins instead of 5 (results unreported). We conclude that a pure scaling is a very reasonable approximation to the data. Table 6, combined with equation (3), is consistent with the view that most of the observed impact of size on bidder announcement returns is due to scaling and that the influence of size as proxy effects is small in comparison.

The prior literature mostly treats bidder size, target size, and relative size as separate variables. An appealing feature of the scaling framework is that it allows us to understand the relation between bidder returns, bidder size, target size, and relative size using one common underlying economic mechanism. Note first that Table 6 shows that the profitability index R does not vary across relative size groups. Taking the derivative with respect ot relative size T/B in equation (2), then yields $\frac{\partial ACAR}{\partial (T/B)} = R$. Hence, we should observe the same pattern, qualitatively, for relative size, as we do for target size, conditional on bidder size. In particular, we should also observe sign flips across subsamples, depending on whether R is on average positive or negative in that sample. Table 4, Panel D, shows that this is in fact what we observe in the data.[7]

In deriving equation (3) we have taken target size as exogenously fixed. Empirically, larger bidders tend to have access to larger targets. As long as the distribution of the size of the targets does not fully rescale with the size of the bidders (which is plausible), the rescaling effect in expression (3) will be there.

[7]In related work, Fuller, Netter, and Stegemoller (2002) and Jansen, Sanning, and Stuart (2013) report that relative size and bidder returns show different relationships across public and private deal subsamples. The former paper proposes to explain these patterns by a specific mix of various interacting size as proxy explanations. The latter paper, like ours, hypothesizes that the sign on the relative size coefficient is determined by the average NPV of a given sample of takeovers. At the same time, that paper explicitly uses bidder size as a proxy for value destruction, thus relying on the "small bidder make better acquisitions" effect we show is inconsistent with the data. Both papers thus advance proxy explanations that are at odds with the results in our paper.

5 Additional Evidence

5.1 Reversals are not specific to the Public/Non-Public Split

A skeptical reader may point out, correctly, that the decision to take over a public or a non-public target is not random. Hence, it is theoretically possible that public and non-public deals differ on some unobservable characteristic, which is itself correlated with bidder returns and the size variable. In this case, the reversals we document across subsamples could be spuriously induced by an omitted variable. While theoretically possible, it is not at all obvious what unobserved variable or mechanism could induce signs to flip for both target and bidder size precisely in the direction predicted by scaling. Moreover, from a conceptual standpoint, if we start with the assumption that the baseline regression on the full sample is well specified, then splitting the sample into public and non-public target subsamples is innocuous, because public status is a regressor in the full sample regression.

Nevertheless, to be conservative, we propose two additional tests to rule out our empirical patterns obtain because public or non-public deals are special. The tests are based on the idea that, under a scaling view, we should also be able to detect reversals *within* subsamples. If we find sign-flips within public and non-public subsamples, these sign-flips cannot be driven by an omitted variable related to the endogenous decision to acquire a public or non-public target. We propose two alternative approaches. The first approach is to suitably define subsamples within subsamples, the second is to analyze the distribution of ACARs directly using quantile regressions.

Evidence from Public Target Cash and Stock Deals. To minimize data mining concerns, we propose to look at the cash and stock payment subsamples within public target deals, which are widely studied throughout the literature. For our present purposes, these subsamples are interesting, because cash deals have small but positive announcement returns (+0.4%), while stock deals have strongly negative returns (−2.7%) as can be seen in Table 2, Panel A. In the language of the framework in Section 4, the sign of R for the average deal differs across these subsamples, and we should therefore expect to see a reversal of sign on the size coefficients across these two subsamples. Table 4, Panel C, shows that this prediction is borne out by the data, which supports the view that our earlier results are not induced by public deals being associated with a particular size pattern for some unobserved reason.

An informative additional finding is that both size coefficients are noticeably smaller for the all cash sample. According to the scaling model in Section 4 effects should be, all else equal, smaller, the closer the sample average return is to zero (i.e., the closer R is to zero). Hence, the smaller coefficients for cash deals are predictions of the scaling model borne out by the data.

Evidence from Quantile Regressions. According to equation (2), a higher profitability index R is associated with a higher bidder announcement return. Intuitively, then, ordering all deals in a sample by bidder announcement return will induce a low, and potentially negative, average R among low ACAR deals, and a high average R for high ACAR deals. If Rs are negative for the lowest ACAR deals and positive for the highest ACAR deals, we should observe size effects with opposite signs in both tails of the ACAR distribution.

We use quantile regressions (e.g., Koenker and Hallock (2001)) to check for the presence of within-subsample reversals.[8] Table 7 presents results for each decile of our dependent variable ACAR. Standard errors are obtained by bootstrapping with 1,000 replications. The table shows we observe the predicted within-subsample reversal pattern for the full sample, as well as for the public and non-public subsamples, separately. Across all specifications the bidder size coefficients are positive and highly significant for low ACAR (i.e., the 10th percentile) and negative and highly significant for high ACAR (i.e., the 90th percentile). We observe exactly the opposite for target size coefficients.

These results strongly support the scaling model and argue against our earlier subsample results being induces by some omitted variable causing the sign flip. In particular, because we now observe reversals within public and non-public subsamples, our earlier results cannot be induced by public and non-public firms being different on some unobserved dimension.

The key points are easier to see in a graph. Figure 2 therefore plots for each decile of the ACAR distribution the coefficients for bidder and target size from the quantile regressions in Table 7. The patterns are visually striking: across all panels, the bidder size coefficient is positive for the lower ACAR quantiles (where ACAR is negative) and negative for higher ACAR quantiles (where ACAR is positive). For target size we find exactly the opposite pattern.

[8] We do not run OLS regressions on subsamples by ACAR, as selection on the dependent variable will, in general, produce biased OLS estimates of the coefficient of interest (e.g., Heckman (1979), Angrist and Pischke (2008)).

Note that the signs on bidder and target size coefficients flip around *the same percentile of the ACAR distribution.* This is informative, because we are not aware of any proxy explanation that would suggest bidder and target size coefficients should flip, let alone flip at the same point. Scaling, on the other hand, can explain why signs flip at the same time. Because the T/B term in equation (2) is multiplied by profitability index R, bidder and target size coefficients always have opposite signs, and they both change signs whenever R changes sign. This is a rather bold prediction that exposes itself to be rejected in the data. But it is not rejected. Figure 2 shows that the prediction is actually describing the data almost perfectly. We view the fact that bidder and target size effects change signs at the same time as one of the strongest pieces of evidence in support of the scaling explanation.

The location of the flipping point is informative. Taken literally, the scaling framework above predicts that the sign-flip should occur at the percentile of the ACAR distribution at which ACAR is zero. For the full sample, this point is at the 46^{th} quantile. Figure 2, Panel (a), shows that the location of the flip in the data is at the 34^{th} quantile. This is lower than predicted, but, arguably, nevertheless in the same ballpark. Given how simple and stylized the scaling model is, this level of accuracy is notable. Perhaps even more importantly, the model makes a prediction on the location of the flipping point for the public subsample relative to the non-public subsample: in the data, ACAR changes sign at a lower percentile for non-public targets, which, in the scaling framework, implies that the sign-flip in the non-public deal subsample should occur "earlier." Panels (b) and (c) show this implication is borne out by the data.

Finally, the scaling framework presented in the previous section predicts that results for relative size should be qualitatively identical to results for target size: negative coefficient estimates for low quantiles of ACAR (value destroying deals with negative R), and positive coefficients for high quantiles. Figure A-1, which we relegate to the Internet Appendix A.1 for brevity, shows exactly this pattern for the full sample as well as the subsamples of non-public and public targets.

5.2 Out-Of-Sample Evidence from European Takeovers

In this section, we analyze the relation between size and bidder announcement returns in Europe. Table A-8, in the Internet Appendix A.2, provides the results when we repeat Table 4, Panel A on the European sample. The results are easily described. For non-public European deals, the average bidder announcement return is 1.6%. The scaling framework thus predicts that we should see a positive coefficient on target size and a negative coefficient on bidder size, consistent with the results in Table A-8.

The public deal subsample, is particularly interesting, because, for European deals, the average bidder announcement return in that group is 0.1%, and therefore of the opposite sign than ACARs in the corresponding U.S. sample. Scaling makes two predictions. First, because the average ACAR is positive, we should observe the *same* signs on bidder and target size as we do for the non-public subsample. Second, because 0.1% is very close to zero, the coefficients on bidder and target size should also be very small. In line with those predictions, we find a positive point estimate for target size, a negative point estimate for bidder size, but both are small and not statistically distinguishable from zero. Using quantile regressions, we also find within subsample reversals for both subsamples in the European data (Figure A-2).

We draw two conclusions. First, the out-of-sample test in this section further supports the scaling framework. Second, the tests in this subsection further support the view that proxy explanations are unable to explain these difference because even if there was a proxy explanation consistent with the sign-flips in the U.S. data (which we doubt), then that proxy explanation would also need to be consistent with the different patterns of signs found in the European data.

6 Conclusion

In this paper, we document a strong reversal pattern in the US takeover data from 1981 to 2014: for public target deals, low bidder returns are associated with small bidders and large targets, while for non-public target deals it is the opposite. Using quantile regressions we show that sign flips also show up within the public and non-public deals subsamples. We argue that these sign-flips constitute a sharp test which rejects all leading explanations in the recent M&A literature for why size matters for bidder announcement returns. Instead, we find that a simple scaling model in which size magnifies a given per-dollar value gain (or loss) can parsimoniously explain the data. We analytically demonstrate that scaling is one of two channels through which size variables can affect bidder announcement returns; the other channel is that size matters because size affects the profitability of a deal directly (size "proxies" for an underlying value driver). The results in our paper suggest that the latter channel, which is the dominant view in the recent literature, cannot explain the reversal patterns, while the scaling channel, which is frequently neglected in the recent literature, can.

Our findings have implications for how we think about value creation in takeovers. For example, consider the stylized "fact" that small bidders make better acquisitions and the associated proxy explanations based on overconfidence or agency problems. This proxy view would suggest that it is important for corporate boards in large firms in particular, to devise procedures, rules, or monitoring arrangements, which limit the decision-making power of their, supposedly overconfident or entrenched, managers on M&A decisions. Moreover, investors should be especially critical of mergers announced by large bidders, and scientists should study why being large implies worse M&A decisions. By contrast, our findings suggest that such conclusions may be unwarranted. While corporate boards are always well advised to think about ways to foster good managerial decisions, the fact that smaller bidders make *worse* acquisitions when the target is a public company speaks directly against the view that large companies always feature particularly bad M&A decision making. For the same reason, investors may want to scrutinize deals by small bidders more when the target is a public firm. An implication for research is that thinking about size variables as proxies for some underlying value driver is not a good way to think about the role size plays for takeover outcomes. Our results indicate that size is important as a scaling factor, but that the core question about which deals create value, rather than destroy value, is one that size is largely uninformative about. Interpreting size as size allows us make progress: we can appreciate the role size plays in scaling dollar returns, and we can focus our energy on understanding better what generates high per-dollar NPV deals.

Finally, our results demonstrate that controlling for target size is important for determining the true incremental impact of bidder size on bidder returns, because bidder and target size are strongly correlated. This stands in contrast to the fact that only 30% of 88 papers in the JF, the JFE, the RFS, and MS (published between 2000 and 2017), which run bidder announcement return regressions include a control for target size.

References

Alexandridis, George, Kathleen P. Fuller, Lars Terhaar, and Nickolaos G. Travlos, 2013, Deal size, acquisition premia and shareholder gains, *Journal of Corporate Finance* 20, 1–13.

Angrist, Joshua, and Jorn-Steffen Pischke, 2008, *Mostly Harmless Econometrics: An Empiricist's Companion* (Princeton University Press).

Asquith, Paul, Robert F Bruner, and David W Mullins, 1983, The gains to bidding firms from merger, *Journal of Financial Economics* 11, 121–139.

Baker, Malcolm, Xin Pan, and Jeffrey Wurgler, 2012, The effect of reference point prices on mergers and acquisitions, *Journal of Financial Economics* 106, 49–71.

Betton, Sandra, B. Espen Eckbo, and Karin S. Thorburn, 2008, Corporate takeovers, *In: The Handbook of Corporate Finance: Empirical Corporate Finance (edited by Espen Eckbo)* New York: Elsevier/North Holland.

Friedman, Milton, 1953, The methodology of positive economics, in *Essays in positive economics* . chap. 1, pp. 3–43 (University of Chicago Press).

Fuller, Kathleen, Jeffry Netter, and Mike Stegemoller, 2002, What do returns to acquiring firms tell us? Evidence from firms that make many acquisitions, *The Journal of Finance* 57, 1763–1793.

Gabaix, Xavier, and Augustin Landier, 2008, Why has CEO pay increased so much?, *The Quarterly Journal of Economics* 123, 49–100.

Gorton, Gary, Matthias Kahl, and Richard J. Rosen, 2009, Eat or be eaten: A theory of mergers and firm size, *Journal of Finance* 64, 1291–1344.

Heckman, James J., 1979, Sample selection bias as a specification error, *Econometrica* 47, 153–161.

Jansen, Ivo, Lee W. Sanning, and Nathan V. Stuart, 2013, On the relation between the relative size of acquisitions and the wealth of acquiring firms, *Applied Economics Letters* 20, 534–539.

Koenker, Roger, and Kevin F. Hallock, 2001, Quantile regression, *The Journal of Economic Perspectives* 15, 143–156.

Malmendier, Ulrike, and Geoffrey Tate, 2015, Behavioral CEOs: The role of managerial overconfidence, *Journal of Economic Perspectives* 29, 37–60.

Masulis, Ronald, Cong Wang, and Fei Xie, 2007, Corporate governance and acquirer returns, *Journal of Finance* 62, 1851–1889.

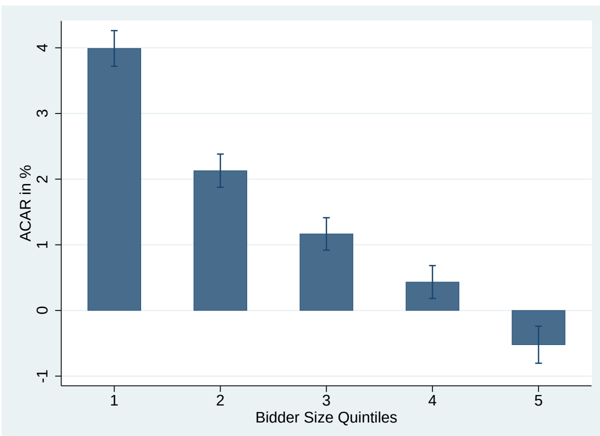
Moeller, Sara B., Frederik P. Schlingemann, and René M. Stulz, 2004, Firm size and the gains from acquisitions, *Journal of Financial Economics* 73, 201–228.

Roll, Richard, 1986, The hubris hypothesis of corporate takeovers, *The Journal of Business* 59, 197–216.

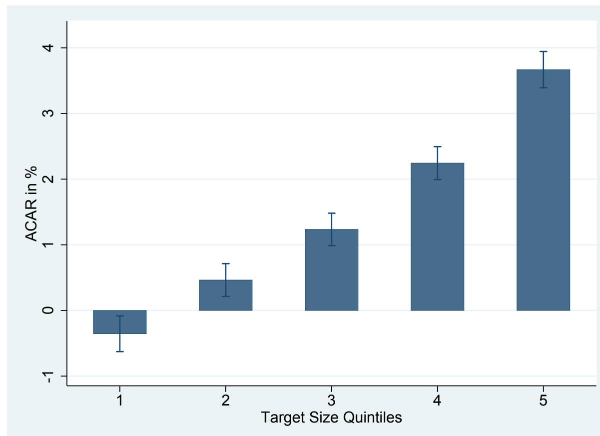
Figure 1: Reversals: Average Bidder Returns Across Size Qunintiles

This figure presents reversal patterns in the data. All subfigures show the average acquirer cumulative abnormal announcement return for five size groups. In subfigure (a), acquirer CARs for non-public target deals are regressed on five bidder market capitalization quintile dummies and the demeaned logarithm of target size, which we measure by deal value. The coefficients for each size quintile dummy (1=smallest and 5=largest) are plotted together with the 95% confidence interval. Subfigure (c) repeats the exercise for public target deals. Subfigures (b) and (d) provide analogous results when we sort the data into target size groups while controlling for bidder size. In Subfigure (c) we present results for two subsamples: (1) all public target deals (navy) and (2) excluding the top relative size decile of public target deals (red).

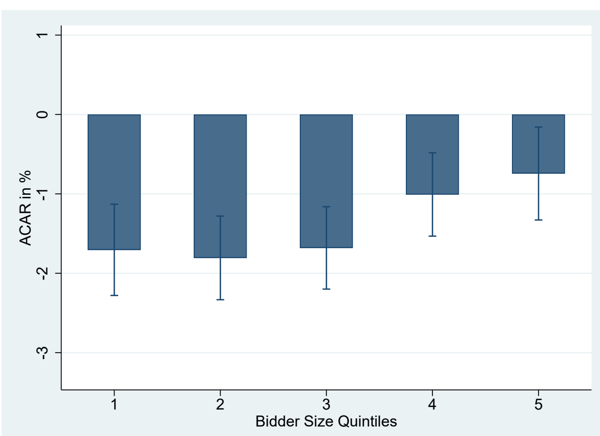
Interpretation: This figure shows that bidder returns for non-public targets decrease (increase) in bidder (target) size and that we observe the opposite pattern for public targets.



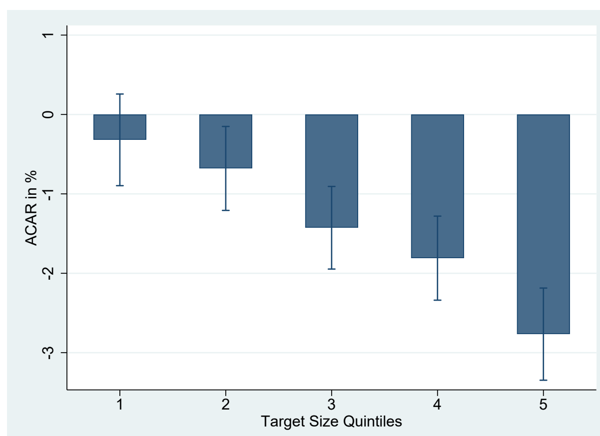
(a) Bidder size effect for non-public targets



(b) Target size effect for non-public targets



(c) Bidder size effect for public targets

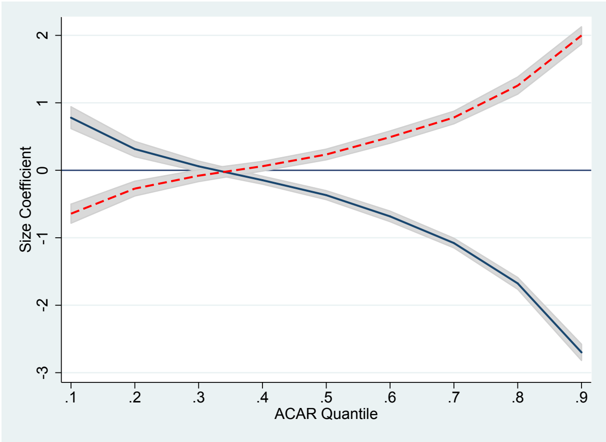


(d) Target size effect for public targets

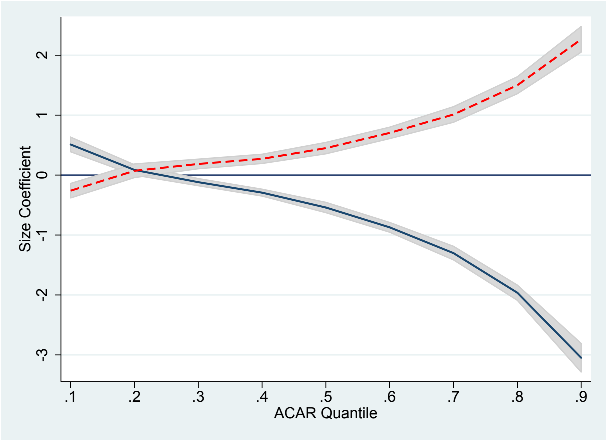
Figure 2: Bidder and Target Size Effect for Different Quantiles of ACAR

This figure shows the bidder and target size coefficients from simultaneous-quantile regressions with three-day abnormal bidder announcement returns as dependent variable. See Table 7 for more details. The blue solid (red dashed) line represents bidder (target) size coefficient estimates. The shaded areas are the respective 95% confidence intervals. Subfigure (a) reports results for for the full sample. Subfigure (b) reports results for non-public targets. Subfigure (c) reports results for public targets.

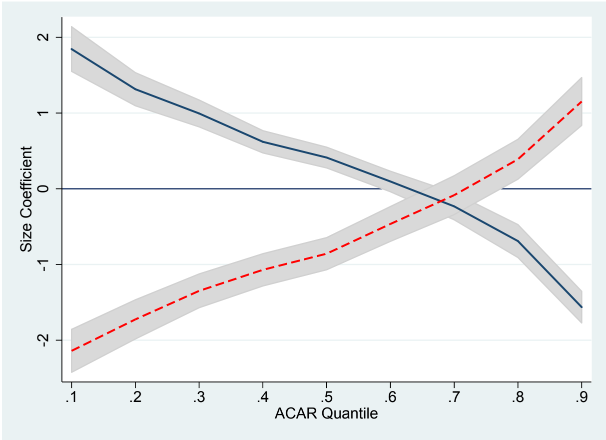
Interpretation: This figure shows that the sign and size of the bidder and target size coefficients depends on the sign and size of the bidder return.



(a) Bidder and target size effect for all targets



(b) Bidder and target size effect for non-public targets



(c) Bidder and target size effect for public targets

Table 2: Summary Statistics

Panel A displays descriptive statistics for the main variables used in our analysis. ACAR are abnormal bidder announcement returns (in %) computed using the $[-1, +1]$ event window and a market model estimated over days $[-280, -31]$. Bidder MCAP is the bidder firm market capitalization at the last fiscal year end before the takeover announcement in million US$. Dealvalue is the total value of the transaction as reported by SDC in million US$. Relative size is the Dealvalue over bidder's market capitalization at the last fiscal year end before the takeover announcement. Bidder BM Ratio is the bidder firm book to market ratio at the last fiscal year end before the takeover announcement. Bidder ROA is the bidder firm return on assets from the last fiscal year before the takeover announcement. Public Target is a dummy variable indicating the target is a public company. Cash (Stock) is a dummy variable indicating that a deal is financed with cash (stock) only. Tender is a dummy variable indicating a tender offer. Hostile is a dummy variable indicating hostile deals. Conglomerate is a dummy variable indicating that bidder and target are in a different 2-digit SIC code industry. Competed is a dummy variable indicating deals with more than one bidder. New Economy is a dummy variable indicating that the target is a new economy firm (SIC codes 3570 to 3579, 3661, 3674, 5045, 5961, or 7370 to 7379). log(Number of Deals) is the natural log of the number of sample transactions in the target's 2-digit SIC code industry in the year of the takeover announcement. R (in %) is ACAR $[-1, +1]$ times Bidder MCAP $[-2]$ divided by Dealvalue. Panel B displays the size distribution of deals across different subsamples.
Interpretation: This table shows summary statistics.

Panel A: Sample Means

Variable	All			Non-Public			Public		
	All	Cash	Stock	All	Cash	Stock	All	Cash	Stock
ACAR	1.04	1.16	0.35	1.44	1.28	1.64	–1.39	0.40	–2.67
Bidder MCAP	2,760.8	3,797.6	3,489.3	1,810.2	2,356.9	1,719.3	8,445.8	12,364.6	7,622.8
Dealvalue	406.4	268.5	731.4	169.3	170.5	153.4	1,824.7	851.7	2,081.2
Relative Size	0.345	0.221	0.498	0.314	0.202	0.500	0.529	0.337	0.494
Bidder BM Ratio	0.614	0.613	0.486	0.617	0.618	0.475	0.593	0.587	0.513
Bidder ROA	0.092	0.122	0.042	0.089	0.119	0.027	0.106	0.138	0.076
Public Target	0.143	0.144	0.300						
Cash	0.237	1.000	0.000	0.236	1.000	0.000	0.238	1.000	0.000
Stock	0.183	0.000	1.000	0.150	0.000	1.000	0.383	0.000	1.000
Tender	0.031	0.079	0.005	0.005	0.011	0.002	0.184	0.481	0.012
Hostile	0.002	0.004	0.001	0.000	0.000	0.000	0.011	0.025	0.003
Conglomerate	0.435	0.431	0.315	0.450	0.431	0.335	0.341	0.430	0.268
Competed	0.010	0.018	0.009	0.003	0.008	0.002	0.049	0.078	0.026
New Economy	0.154	0.174	0.233	0.154	0.167	0.252	0.157	0.214	0.186
log(Number of Deals)	4.222	4.188	4.710	4.225	4.222	4.741	4.207	3.987	4.638
R	4.65	6.55	–0.44	6.84	8.02	6.27	–8.27	–2.04	–15.91
N	26,890	6,363	4,923	23,038	5,447	3,447	3,852	916	1,476

Panel B: Size Distribution

Type of deal	Number of Deals	% of All	Avg. Deal Value	Total Deal Value	% of All
All	26,890	100.0	406.4	10,928,096	100.0
Non-Public	23,038	85.7	169.3	3,900,333	35.7
Private	13,547	50.4	100.1	1,356,055	12.4
Subsidiary	8,107	30.1	253.0	2,051,071	18.8
Public	3,852	14.3	1,824.7	7,028,744	64.3
Public All Cash	916	3.4	851.7	780,157	7.1
Public All Stock	1,476	5.5	2,081.2	3,071,851	28.1
Public Mix	1460	5.4	2,175.8	3,176,668	29.1

Table 3: Size Sorts for Non-Public Targets

This table displays average three-day abnormal bidder announcement returns across size quintiles for non-public target deals. In Panel A (B) deals are sorted annually according to bidder market capitalization (deal value). In Panel C (D) deals are first sorted annually into quintiles according to deal value (bidder market capitalization). Then, within each deal value (bidder market capitalization) quintile, we sort deals into quintiles of bidder market capitalization (deal value). Panel C (D) then presents for each bidder market capitalization (deal value) quintile the average across all deal value (bidder market capitalization) quintiles. The complete 5×5 matrix is reported in the Internet Appendix A.2, Table A-3. For each size quintile the average ACAR (in %), bidder size (in million US$), target size (in million US$), and relative size are reported. For each quintile, the T-statistic on whether ACAR is equal to zero and the number of observations are also shown. The table also reports the difference between the lowest and the highest size quintile and the associated T-statistic from the two-sample (equality of coefficients) T-test.

Interpretation: This table shows that bidder returns for non-public targets decrease (increase) in bidder (target) size.

Panel A: Sort by Bidder Size

Quintile	1	2	3	4	5	5 – 1
ACAR	3.06	1.68	1.12	0.78	0.58	–2.48
N	4,632	4,609	4,599	4,610	4,588	
T-stat	16.85	11.88	10.42	8.18	7.12	–12.44
Bidder Size	60.6	211.1	493.1	1,119.4	7,197.4	
Target Size	31.3	54.5	97.0	155.3	510.6	
Relative Size	0.819	0.292	0.217	0.145	0.094	

Panel B: Sort by Target Size

Quintile	1	2	3	4	5	5 – 1
ACAR	1.24	1.09	1.26	1.60	2.02	0.78
N	4,664	4,625	4,568	4,600	4,581	
T-stat	9.68	10.20	12.01	10.87	14.23	4.09
Bidder Size	189.1	456.4	841.1	1,690.6	5,913.9	
Target Size	7.1	20.7	45.3	107.4	670.4	
Relative Size	0.116	0.179	0.245	0.326	0.710	

Panel C: Double-Sort – First by Target Size then by Bidder Size

Quintile	1	2	3	4	5	5 – 1
ACAR	3.85	1.66	0.95	0.45	0.25	–3.60
N	4,688	4,616	4,617	4,603	4,514	
T-stat	19.07	14.30	9.77	5.11	3.06	–16.29
Bidder Size	147.5	410.3	822.5	1,720.2	6,070.6	
Target Size	117.7	128.4	138.4	169.6	296.1	
Relative Size	1.086	0.240	0.124	0.069	0.032	

Panel D: Double-Sort – First by Bidder Size then by Target Size

Quintile	1	2	3	4	5	5 – 1
ACAR	0.53	0.92	1.08	1.44	3.30	2.76
N	4,713	4,598	4,607	4,602	4,518	
T-stat	5.39	8.55	10.25	12.87	17.37	13.06
Bidder Size	937.5	1,207.6	1,454.8	1,947.3	3,556.7	
Target Size	18.2	39.1	71.5	136.8	592.3	
Relative Size	0.041	0.085	0.145	0.260	1.060	

Table 4: Size and Bidder Announcement Returns: Regression Results

This table presents results for OLS regressions of three-day abnormal bidder announcement returns on bidder size, target size, and control variables for the full sample, only non-public targets, and only public targets. All variables have previously been defined in Table 2. Bidder MCAP and Dealsize are in logs. In Panel B, C, and D, the control variables from Panel A are included, but not shown. Panel B includes additional bidder and target industry times year fixed effects. Panel C only includes public targets acquired using only cash or only stock. Panel D uses log of relative size instead of bidder and target size. The T-statistics are reported in small font size below the estimates. Standard errors are clustered by announcement month.
Interpretation: This table shows that bidder returns for non-public targets decrease (increase) in bidder (target) size and that both signs flip for public targets.

Panel A: Baseline

Dep. var.:	ACAR $[-1, +1]$					
	All Targets		Non-Public Targets		Public Targets	
	(1)	(2)	(3)	(4)	(5)	(6)
Bidder MCAP	–0.474	–0.950	–0.522	–1.201	–0.185	0.268
	–11.75	–11.40	–11.49	–12.88	–2.34	2.27
Dealvalue		0.752		1.072		–0.747
		7.70		9.73		–5.50
Public Target	–2.411	–3.341				
	–10.98	–14.06				
Bidder ROA	0.028	0.025	0.201	0.225	1.392	1.382
	0.03	0.03	0.20	0.23	0.60	0.61
Bidder BM Ratio	0.400	0.175	0.458	0.133	0.422	0.621
	2.18	0.95	2.40	0.70	0.96	1.39
Cash	0.191	0.341	–0.031	0.098	1.818	1.274
	1.61	3.00	–0.25	0.82	5.93	4.03
Stock	–0.009	–0.070	0.451	0.376	–0.854	–0.873
	–0.04	–0.35	1.92	1.62	–2.99	–3.05
Tender	1.650	1.701	1.457	1.317	0.807	0.890
	4.02	3.98	1.11	0.91	2.13	2.35
Hostile	0.424	–0.447			0.091	1.034
	0.55	–0.56			0.11	1.26
Conglomerate	–0.113	–0.044	–0.139	–0.061	–0.439	–0.564
	–0.74	–0.28	–0.80	–0.35	–1.42	–1.85
Competed	0.755	0.427	4.249	4.020	–0.841	–0.468
	0.73	0.39	1.79	1.49	–1.37	–0.79
New Economy	–0.616	–0.556	–0.560	–0.482	–0.995	–1.048
	–2.33	–2.09	–1.94	–1.67	–1.37	–1.45
log(Number of Deals)	–0.360	–0.326	–0.233	–0.156	–0.948	–0.841
	–2.74	–2.44	–1.65	–1.08	–2.86	–2.54
Adjusted R^2	0.035	0.044	0.020	0.039	0.076	0.088
Number of observations	23,916	23,916	20,231	20,231	3,685	3,685
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Fixed Effects

Dep. var.:	ACAR $[-1,+1]$					
	All Targets		Non-Public Targets		Public Targets	
	(1)	(2)	(3)	(4)	(5)	(6)
Bidder MCAP	–0.937	–0.944	–1.223	–1.226	0.521	0.497
	–10.03	–10.57	–11.50	–11.91	3.94	3.63
Dealvalue	0.737	0.780	1.100	1.133	–1.022	–0.982
	7.06	6.94	9.03	8.79	–6.53	–5.82
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bidder Ind. x Year FE	Yes	No	Yes	No	Yes	No
Target Ind. x Year FE	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.034	0.033	0.026	0.025	0.140	0.100
Number of observations	23,916	23,921	20,231	20,236	3,685	3,685

Panel C: Public All Cash vs. All Stock

Dep. var.:	ACAR $[-1,+1]$			
	Public All Cash		Public All Stock	
	(1)	(2)	(3)	(4)
Bidder MCAP	–0.563	–0.612	0.217	1.041
	–4.19	–2.76	1.52	5.58
Dealvalue		0.095		–1.267
		0.34		–5.51
Controls	Yes	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.100	0.099	0.088	0.121
Number of observations	898	898	1,418	1,418

Panel D: Relative Size

Dep. var.:	ACAR $[-1,+1]$		
	All Targets	Non-Public Targets	Public Targets
	(1)	(2)	(3)
log(Relative Size)	0.861	1.142	–0.451
	9.84	11.61	–3.84
Controls	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes
Adjusted R^2	0.043	0.038	0.081
Number of observations	23,916	20,231	3,685

Table 5: Size Sorts for Public Targets

This table displays average three-day abnormal bidder announcement returns across size quintiles for public target deals. In Panel A (B) deals are sorted annually according to bidder market capitalization (deal value). In Panel C (D) deals are first sorted annually into quintiles according to deal value (bidder market capitalization). Then, within each deal value (bidder market capitalization) quintile, we sort deals into quintiles of bidder market capitalization (deal value). Panel C (D) then presents for each bidder market capitalization (deal value) quintile the average across all deal value (bidder market capitalization) quintiles. The complete 5×5 matrix is reported in the Internet Appendix A.2, Table A-3. For each size quintile the average ACAR (in %), bidder size (in million US$), target size (in million US$), and relative size are reported. For each quintile, the T-statistic on whether ACAR is equal to zero and the number of observations are also shown. The table also reports the difference between the lowest and the highest size quintile and the associated T-statistic from the two-sample (equality of coefficients) T-test.

Interpretation: This table shows that bidder returns for public targets increase (decrease) in bidder (target) size once we control for target (bidder) size.

Panel A: Sort by Bidder Size

Quintile	1	2	3	4	5	5 - 1
ACAR	–0.71	–1.44	–1.70	–1.39	–1.74	–1.03
N	785	770	768	779	750	
T-stat	–2.04	–5.03	–6.75	–6.32	–9.12	–2.58
Bidder Size	203.8	749.9	2,069.3	5,899.1	34,148.3	
Target Size	169.3	423.5	934.2	1,686.8	6,050.9	
Relative Size	0.725	0.414	0.290	0.201	0.148	

Panel B: Sort by Target Size

Quintile	1	2	3	4	5	5 - 1
ACAR	–0.37	–0.70	–1.42	–1.79	–2.72	–2.34
N	784	771	768	771	758	
T-stat	–1.57	–2.45	–5.30	–7.01	–9.87	–6.45
Bidder Size	883.0	2,424.3	5,083.0	9,926.0	24,294.4	
Target Size	58.9	173.6	390.5	1,018.0	7,604.1	
Relative Size	0.306	0.304	0.271	0.385	0.520	

Panel C: Double-Sort – First by Target Size then by Bidder Size

Quintile	1	2	3	4	5	5 - 1
ACAR	–1.56	–1.62	–1.76	–1.20	–0.73	0.83
N	842	769	784	768	689	
T-stat	–4.28	–5.73	–7.45	–6.23	–4.46	2.03
Bidder Size	762.5	1,757.4	3,871.3	9,013.2	29,873.1	
Target Size	950.5	1,183.6	1,478.7	1,998.8	3,808.0	
Relative Size	0.908	0.382	0.234	0.120	0.058	

Panel D: Double-Sort – First by Bidder Size then by Target Size

Quintile	1	2	3	4	5	5 - 1
ACAR	–0.37	–0.92	–1.21	–2.34	–2.30	–1.93
N	840	769	779	766	698	
T-stat	–2.21	–4.06	–5.10	–7.14	–6.52	–5.33
Bidder Size	5,097.5	6,790.4	9,562.0	8,784.5	12,681.6	
Target Size	147.2	352.6	720.0	1,675.9	6,861.4	
Relative Size	0.158	0.161	0.258	0.409	0.855	

Table 6: Size Quintiles and Profitability Index

This table presents results for OLS regressions of the profitability index (R in %) on bidder, target, and relative size quintile dummies. The first quintile is always omitted. All regressions contain the same set of control variables as is used in Table 4 but not are reported to conserve space. All variables have previously been defined in Table 2. In Columns (1) to (4) the full sample, in Column (5) only non-public targets, and in Column (6) only public targets are used. The T-statistics are reported in small font size below the estimates. **Interpretation:** This table shows that the profitability index R is not significantly correlated with bidder, target or relative size.

Dep. var.:	Profitability Index (R in %)					
	All Targets				Non-Public	Public
	(1)	(2)	(3)	(4)	(5)	(6)
BidderSize2	1.555			2.134	2.643	–2.270
	0.43			0.51	0.58	–0.47
BidderSize3	0.253			1.525	1.751	–1.906
	0.07			0.31	0.33	–0.29
BidderSize4	2.004			4.320	4.721	1.125
	0.47			0.72	0.71	0.14
BidderSize5	2.152			6.546	10.668	–6.705
	0.50			1.00	1.38	–0.87
TargetSize2		0.801		–0.024	0.155	–21.138
		0.15		0.00	0.03	–0.66
TargetSize3		–0.074		–1.676	–2.069	–23.109
		–0.01		–0.28	–0.34	–0.74
TargetSize4		0.332		–2.214	–3.318	–22.759
		0.07		–0.37	–0.53	–0.70
TargetSize5		–4.218		–8.103	–8.204	–27.381
		–0.87		–1.17	–1.09	–0.83
RelativeSize2			2.141			
			0.35			
RelativeSize3			3.847			
			0.67			
RelativeSize4			3.066			
			0.53			
RelativeSize5			2.199			
			0.37			
Constant	–0.025	0.878	–1.166	–0.143	–9.453	31.173
	0.00	0.02	–0.03	0.00	–0.23	1.04
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	–0.001	–0.001	–0.001	–0.001	–0.003	0.004
Number of observations	23,520	23,520	23,520	23,520	19,863	3,657

Table 7: Size and Bidder Announcement Returns: Quantile Regression Results

This table presents results for simultaneous-quantile regressions of three-day abnormal bidder announcement returns on bidder size, target size, and control variables. Bidder MCAP and Dealsize are in logs. Control variables (not reported) are the same as in Table 4. All variables have previously been defined in Table 2. Columns (3) and (4) present results for subsamples. The T-statistics are reported in small font size below the estimates. Standard errors are obtained via bootstrapping (1000 replications).

Interpretation: This table shows that the sign and size of the bidder and target size coefficients depends on the sign and size of the bidder return.

Dep. var.:	ACAR $[-1,+1]$			
	All	All	Non-public	Public
	(1)	(2)	(3)	(4)
10th Percentile ACAR	–6.02	–6.02	–5.33	–8.98
Bidder MCAP	0.317	0.780	0.511	1.845
	7.29	11.21	7.10	11.34
Dealvalue		–0.643	–0.260	–2.141
		–8.93	–3.35	–14.48
20th Percentile ACAR	–3.19	–3.19	–2.77	–5.58
Bidder MCAP	0.122	0.315	0.086	1.315
	4.48	6.47	1.99	11.51
Dealvalue		–0.271	0.072	–1.725
		–5.34	1.38	–14.01
30th Percentile ACAR	–1.64	–1.64	–1.33	–3.62
Bidder MCAP	0.004	0.059	–0.118	0.995
	0.18	1.73	–3.57	9.72
Dealvalue		–0.080	0.186	–1.348
		–2.13	4.88	–13.96
40th Percentile ACAR	–0.59	–0.59	–0.36	–2.21
Bidder MCAP	–0.107	–0.147	–0.293	0.620
	–5.83	–5.45	–9.51	6.66
Dealvalue		0.060	0.271	–1.071
		1.86	7.36	–10.46
50th Percentile ACAR	0.35	0.35	0.58	–1.05
Bidder MCAP	–0.222	–0.369	–0.541	0.412
	–10.02	–11.71	–13.19	5.10
Dealvalue		0.234	0.450	–0.857
		6.76	10.05	–9.37
60th Percentile ACAR	1.41	1.41	1.67	0.04
Bidder MCAP	–0.358	–0.683	–0.872	0.096
	–15.19	–18.58	–21.87	1.30
Dealvalue		0.492	0.704	–0.465
		12.37	15.89	–4.90
70th Percentile ACAR	2.71	2.71	3.00	1.13
Bidder MCAP	–0.549	–1.078	–1.302	–0.232
	–20.54	–25.18	–24.60	–2.45
Dealvalue		0.782	1.011	–0.085
		17.36	16.81	–0.76
80th Percentile ACAR	4.70	4.70	5.11	2.62
Bidder MCAP	–0.881	–1.676	–1.962	–0.691
	–23.07	–30.61	–30.90	–6.39
Dealvalue		1.256	1.499	0.390
		22.62	21.50	3.14
90th Percentile ACAR	8.94	8.94	9.44	5.44
Bidder MCAP	–1.411	–2.699	–3.047	–1.563
	–24.34	–36.22	–34.93	–10.03
Dealvalue		1.999	2.265	1.153
		27.54	24.19	6.25
Number of observations	23,921	23,921	20,236	3,685

Internet Appendix for

"Bidder and Target Size Effects in M&A Are Not Driven by Overconfidence or Agency Problems"

CHRISTOPH SCHNEIDER and OLIVER SPALT[‡‡]

This appendix presents additional results to accompany the paper "Bidder and Target Size Effects in M&A Do Not Reflect Overconfidence or Agency Problems" The contents are:

Section A.1 presents additional figures mentioned in the paper.

Section A.2 presents additional tables mentioned in the paper.

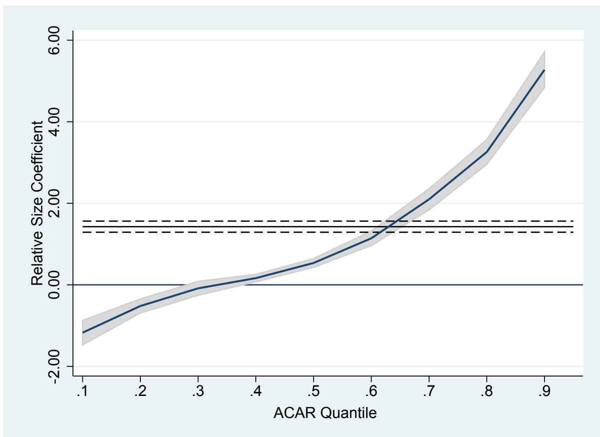
Section A.3 presents additional information on our M&A literature survey mentioned in the paper.

[‡‡]Citation format: Schneider, Christoph, and Oliver Spalt, 2021, Internet Appendix to "Bidder and Target Size Effects in M&A Are Not Driven by Overconfidence or Agency Problems"

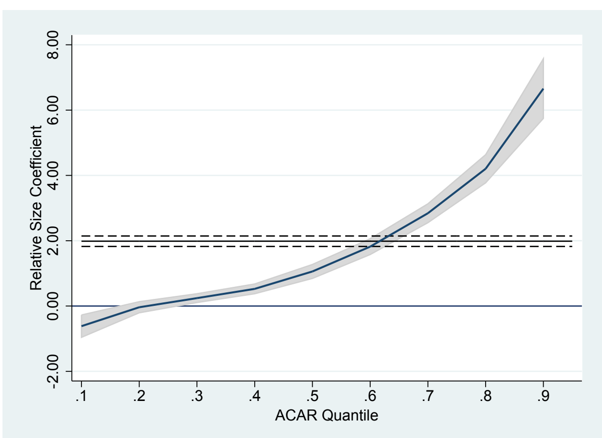
A.1 Additional Figures

Figure A-1: Relative Size Effect for Different Quantiles of ACAR

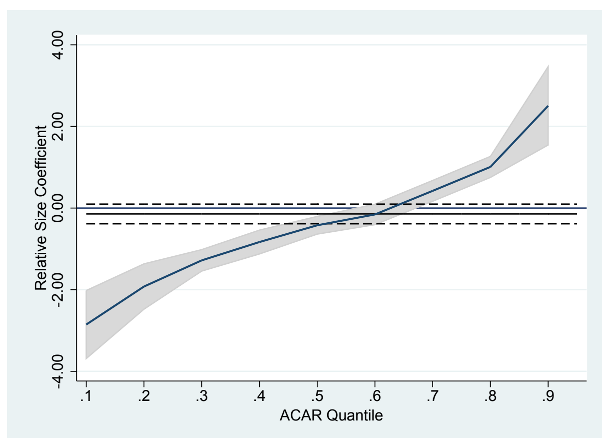
This figure shows the relative size coefficient (= Dealvalue / Bidder MCAP) from simultaneous-quantile regressions with three-day abnormal bidder announcement returns as dependent variable. The same set of control variables as in Table 4 is used but the bidder and target size variables are omitted. Because of some extreme outliers relative size is winsorized at the 1st and 99th percentile. The shaded area are the 95% confidence intervals. The black solid line represents the OLS coefficient estimate and the dashed lines its 95% confidence interval. Subfigure (a) reports results for the full sample, subfigure (b) for non-public targets, and subfigure (c) for public targets.



(a) Relative size effect for all targets



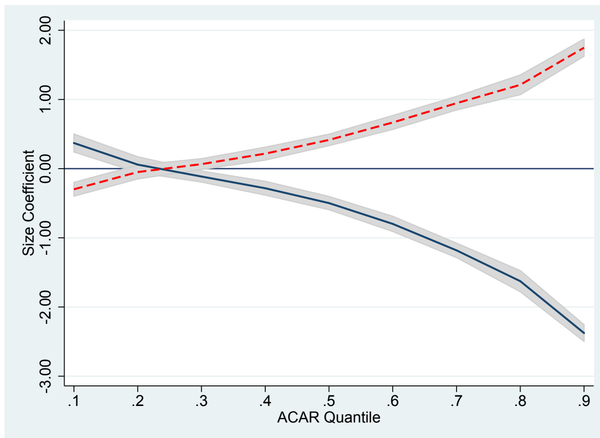
(b) Relative size effect for non-public targets



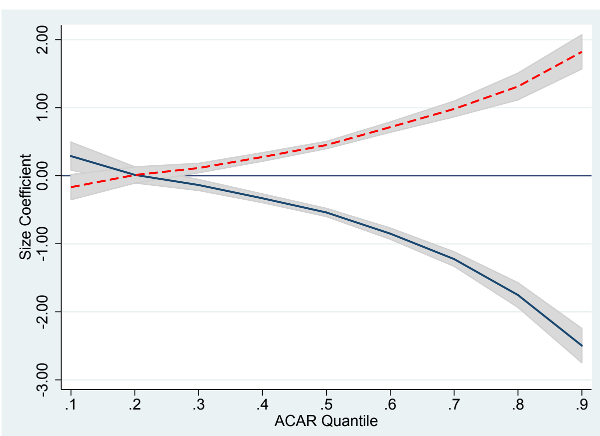
(c) Relative size effect for public targets

Figure A-2: Bidder and Target Size Effect for Different Quantiles of ACAR with European Data

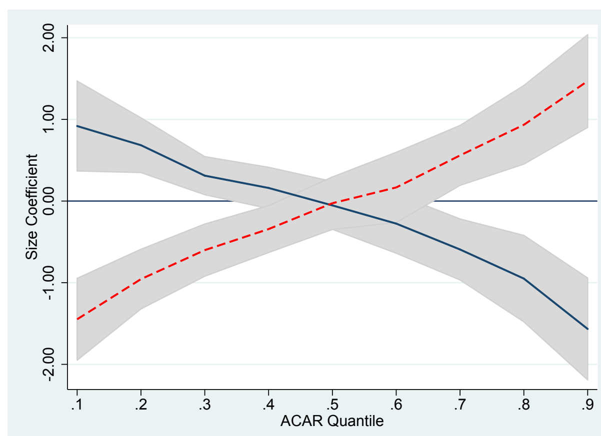
This figure shows the bidder and target size coefficients from simultaneous-quantile regressions with three-day abnormal bidder announcement returns as dependent variable for a European takeover sample. See Table A-8 for more details on the sample. The blue solid (red dashed) line represents bidder (target) size coefficient estimates. The shaded areas are the respective 95% confidence intervals. Subfigure (a) reports results for for the full sample. Subfigure (b) reports results for non-public targets. Subfigure (c) reports results for public targets.



(a) Bidder and target size effect for all targets



(b) Bidder and target size effect for non-public targets



(c) Bidder and target size effect for public targets

A.2 Additional Tables

Table A-1: Sample Distribution

This table displays for three samples (all targets, only non-public targets, and only public targets) the annual number of deals and the annual average bidder announcement returns computed using the $[-1,+1]$ event window and a market model estimated over days $[-280,-31]$.

Year	All Targets		Non-Public Targets		Public Targets	
	ACAR	N	ACAR	N	ACAR	N
1981	–0.17	335	0.21	245	–1.18	90
1982	0.12	381	0.33	318	–0.93	63
1983	0.53	542	0.74	471	–0.86	71
1984	0.86	604	0.91	506	0.60	98
1985	–0.23	281	0.46	190	–1.66	91
1986	0.84	412	1.15	327	–0.33	85
1987	1.33	344	1.87	268	–0.58	76
1988	0.29	363	0.41	291	–0.19	72
1989	0.61	450	0.76	391	–0.36	59
1990	0.63	383	0.86	345	–1.50	38
1991	1.29	440	1.63	385	–1.07	55
1992	2.05	661	2.42	599	–1.56	62
1993	2.44	961	2.84	861	–1.09	100
1994	1.39	1,185	1.76	1,026	–0.99	159
1995	1.33	1,258	1.79	1,050	–0.97	208
1996	1.84	1,520	2.23	1,298	–0.40	222
1997	1.21	2,066	1.52	1,778	–0.76	288
1998	0.88	2,059	1.46	1,769	–2.64	290
1999	0.94	1,470	1.67	1,200	–2.30	270
2000	0.61	1,132	1.59	923	–3.75	209
2001	0.16	802	1.09	646	–3.69	156
2002	1.17	770	1.50	689	–1.56	81
2003	0.42	806	1.03	683	–2.94	123
2004	0.77	894	1.25	761	–1.96	133
2005	0.74	978	1.09	867	–2.05	111
2006	0.61	977	0.90	856	–1.42	121
2007	1.08	866	1.41	746	–0.98	120
2008	0.53	516	0.83	464	–2.19	52
2009	1.41	388	1.78	329	–0.61	59
2010	0.89	543	1.03	482	–0.25	61
2011	0.54	555	0.68	511	–1.04	44
2012	1.14	655	1.15	588	1.02	67
2013	1.65	611	1.66	546	1.56	65
2014	1.90	682	1.89	629	2.02	53
1981-2014	1.04	26,890	1.44	23,038	–1.39	3,852

Table A-2: Summary Statistics

This table displays additional descriptive statistics for the main variables used in our analysis in the full sample (Panel A), the sample of non-public target deals (Panel B), and the sample of public target deals (Panel C). All variables have previously been defined in Table 2.

Panel A: Sample Statistics – All

Variable	Mean	Median	Std	Min	P25	P75	Max	N
ACAR	1.04	0.30	8.53	–73.96	–2.23	3.34	365.31	26,890
Bidder MCAP	2,760.8	512.9	11,866.1	0.8	155.8	1,631.2	446,490.4	26,890
Dealvalue	406.4	51.9	2,948.9	1.0	17.3	182.7	226,489.6	26,890
Relative Size	0.345	0.105	2.660	0.010	0.041	0.282	380.278	26,890
Bidder BM Ratio	0.614	0.516	0.499	0.000	0.317	0.777	11.749	26,186
Bidder ROA	0.092	0.108	0.166	–3.506	0.031	0.168	1.776	24,439
Public Target	0.143	0.000	0.350	0.000	0.000	0.000	1.000	26,890
Cash	0.237	0.000	0.425	0.000	0.000	0.000	1.000	26,890
Stock	0.183	0.000	0.387	0.000	0.000	0.000	1.000	26,890
Tender	0.031	0.000	0.173	0.000	0.000	0.000	1.000	26,890
Hostile	0.002	0.000	0.041	0.000	0.000	0.000	1.000	26,890
Conglomerate	0.435	0.000	0.496	0.000	0.000	1.000	1.000	26,890
Competed	0.010	0.000	0.099	0.000	0.000	0.000	1.000	26,890
New Economy	0.154	0.000	0.361	0.000	0.000	0.000	1.000	26,868
log(Number of Deals)	4.222	4.369	1.262	0.000	3.466	5.124	6.568	26,890
R	4.65	1.70	189.84	–5,333.18	–21.24	31.09	5,588.52	26,319

Panel B: Sample Statistics – Non-Public

Variable	Mean	Median	Std	Min	P25	P75	Max	N
ACAR	1.44	0.48	8.64	–73.96	–1.88	3.62	365.31	23,038
Bidder MCAP	1,810.2	436.8	7,253.9	0.8	135.7	1,295.3	313,042.3	23,038
Dealvalue	169.3	40.0	922.9	1.0	14.6	123.6	96,300.0	23,038
Relative Size	0.314	0.093	2.847	0.010	0.038	0.237	380.278	23,038
Bidder BM Ratio	0.617	0.516	0.510	0.000	0.320	0.779	11.749	22,388
Bidder ROA	0.089	0.108	0.172	–3.506	0.031	0.167	1.776	20,717
Cash	0.236	0.000	0.425	0.000	0.000	0.000	1.000	23,038
Stock	0.150	0.000	0.357	0.000	0.000	0.000	1.000	23,038
Tender	0.005	0.000	0.072	0.000	0.000	0.000	1.000	23,038
Hostile	0.000	0.000	0.000	0.000	0.000	0.000	0.000	23,038
Conglomerate	0.450	0.000	0.498	0.000	0.000	1.000	1.000	23,038
Competed	0.003	0.000	0.057	0.000	0.000	0.000	1.000	23,038
New Economy	0.154	0.000	0.361	0.000	0.000	0.000	1.000	23,018
log(Number of Deals)	4.225	4.369	1.265	0.000	3.466	5.124	6.568	23,038
R	6.84	3.33	202.20	–5,333.18	–21.44	36.54	5,588.52	22,500

Panel C: Sample Statistics – Public

Variable	Mean	Median	Std	Min	P25	P75	Max	N
ACAR	–1.39	–1.05	7.39	–49.92	–4.51	1.79	104.02	3,852
Bidder MCAP	8,445.8	1,751.8	25,112.7	6.0	467.0	5,696.1	446,490.4	3,852
Target MCAP	1,223.0	210.2	5,170.9	2.8	74.5	699.2	117,241.0	3,718
Dealvalue	1,824.7	327.8	7,299.1	3.0	118.3	1,106.8	226,489.6	3,852
Relative Size	0.529	0.251	0.937	0.010	0.084	0.640	22.660	3,852
Bidder BM Ratio	0.593	0.509	0.428	0.000	0.310	0.767	5.916	3,798
Bidder ROA	0.106	0.108	0.128	–2.918	0.030	0.172	0.763	3,722
Cash	0.238	0.000	0.426	0.000	0.000	0.000	1.000	3,852
Stock	0.383	0.000	0.486	0.000	0.000	1.000	1.000	3,852
Tender	0.184	0.000	0.387	0.000	0.000	0.000	1.000	3,852
Hostile	0.011	0.000	0.105	0.000	0.000	0.000	1.000	3,852
Conglomerate	0.341	0.000	0.474	0.000	0.000	1.000	1.000	3,852
Competed	0.049	0.000	0.216	0.000	0.000	0.000	1.000	3,852
New Economy	0.157	0.000	0.364	0.000	0.000	0.000	1.000	3,850
log(Number of Deals)	4.207	4.369	1.242	0.000	3.434	5.075	6.568	3,852
R	–8.27	–3.96	85.48	–1,247.66	–20.74	8.45	867.35	3,819

Table A-3: Double-Sorts for Non-Public and Public Targets

This table displays average three-day abnormal bidder announcement returns across size quintiles for non-public (Panel A and B) and public (Panel C and D) target deals. In Panel A and C (B and D) deals are first sorted annually into quintiles according to deal value (bidder market capitalization). Then, within each deal value (bidder market capitalization) quintile, we sort deals into quintiles of bidder market capitalization (deal value). For each size quintile portfolio the average ACAR (in %) and the number of observations (in smaller font size) is reported. The second to last line in each panel reports the observation weighted average ACAR (in %) across all quintiles in a column. The last line reports the total number of observations in each column.

Panel A: Double-Sort Non-Public Targets – First by Target Size then by Bidder Size

	Bidder Size Quintile					
Target Size Quintile	1	2	3	4	5	5–1
1	3.36	1.46	0.91	0.35	0.05	–3.31
	953	936	936	922	917	
2	3.04	1.22	0.54	0.15	0.47	–2.57
	940	928	927	918	912	
3	3.15	1.62	0.99	0.40	0.09	–3.07
	928	916	912	921	891	
4	4.32	1.88	0.69	0.60	0.46	–3.86
	937	919	924	921	899	
5	5.37	2.11	1.61	0.77	0.18	–5.19
	930	917	918	921	895	
Weighted average	3.85	1.66	0.95	0.45	0.25	–3.60
	4,688	4,616	4,617	4,603	4,514	

Panel B: Double-Sort Non-Public Targets – First by Bidder Size then by Target Size

	Target Size Quintile					
Bidder Size Quintile	1	2	3	4	5	5–1
1	1.61	2.51	2.68	2.69	5.87	4.26
	947	925	929	920	911	
2	0.22	1.04	0.90	1.71	4.63	4.42
	940	925	918	924	902	
3	0.25	0.30	0.99	1.36	2.73	2.48
	949	909	927	915	899	
4	0.14	0.33	0.64	0.74	2.06	1.92
	938	923	919	927	903	
5	0.44	0.42	0.17	0.68	1.18	0.73
	939	916	914	916	903	
Weighted average	0.53	0.92	1.08	1.44	3.30	2.76
	4,713	4,598	4,607	4,602	4,518	

Panel C: Double-Sort Public Targets – First by Target Size then by Bidder Size

	Bidder Size Quintile					
Target Size Quintile	1	2	3	4	5	5–1
1	0.14	–0.60	–0.56	–0.47	–0.43	–0.57
	171	156	158	157	142	
2	–0.30	–1.19	–1.60	–0.27	–0.07	0.23
	168	154	159	151	139	
3	–2.26	–0.97	–1.36	–1.24	–1.17	1.10
	168	152	159	151	138	
4	–1.91	–2.99	–2.31	–1.16	–0.37	1.54
	168	156	156	156	135	
5	–3.49	–2.35	–3.03	–2.87	–1.64	1.85
	167	151	152	153	135	
Weighted average	–1.56	–1.62	–1.76	–1.20	–0.73	0.83
	842	769	784	768	689	

Panel D: Double-Sort Public Targets – First by Bidder Size then by Target Size

	Target Size Quintile					
Bidder Size Quintile	1	2	3	4	5	5–1
1	0.11	–0.38	–1.04	–1.67	–0.63	–0.75
	170	157	158	157	143	
2	–0.67	–1.55	–1.13	–1.58	–2.44	–1.77
	168	153	158	152	139	
3	–0.45	–0.76	–1.53	–3.17	–2.84	–2.39
	168	152	157	152	139	
4	–0.05	–1.23	–0.80	–2.37	–2.73	–2.69
	169	157	156	156	141	
5	–0.83	–0.67	–1.56	–2.95	–2.91	–2.08
	165	150	150	149	136	
Weighted average	–0.37	–0.92	–1.21	–2.34	–2.30	–1.93
	840	769	779	766	698	

Table A-4: Size and Bidder Announcement Returns: Regression Results for Serial Acquirers

This table presents results for OLS regressions of three-day abnormal bidder announcement returns on bidder size, target size, and control variables for the full sample, only non-public targets, and only public targets of serial acquirers (defined as in Fuller, Netter, and Stegemoeller (2002), at least five acquisitions within any three year period). All variables have previously been defined in Table 2. Bidder MCAP and Dealsize are in logs. The T-statistics are reported in small font size below the estimates. Standard errors are clustered by announcement month.

Dep. var.:	ACAR $[-1, +1]$					
	All Targets		Non-Public Targets		Public Targets	
	(1)	(2)	(3)	(4)	(5)	(6)
Bidder MCAP	–0.264	–0.485	–0.353	–0.872	0.243	1.061
	–2.99	–3.54	–3.59	–5.87	1.18	4.86
Dealvalue		0.339		0.779		–1.481
		2.70		5.98		–5.78
Public Target	–2.753	–3.167				
	–8.36	–9.98				
Bidder ROA	–1.597	–1.476	–1.032	–0.744	–3.053	–3.407
	–0.35	–0.32	–0.21	–0.15	–0.45	–0.52
Bidder BM Ratio	0.024	–0.062	–0.168	–0.367	2.084	2.461
	0.07	–0.18	–0.41	–0.93	1.67	2.08
Cash	–0.091	–0.027	–0.257	–0.166	1.049	–0.170
	–0.37	–0.12	–0.95	–0.64	1.38	–0.23
Stock	–0.324	–0.377	0.018	–0.090	–0.802	–0.806
	–1.07	–1.24	0.05	–0.25	–1.14	–1.18
Tender	1.617	1.680	3.168	3.061	–0.169	–0.119
	2.07	2.13	1.74	1.64	–0.21	–0.15
Hostile	1.144	0.793			3.738	4.161
	0.33	0.22			1.01	1.23
Conglomerate	0.255	0.274	0.295	0.324	–0.150	–0.578
	0.94	1.01	0.97	1.07	–0.20	–0.79
Competed	4.081	4.009	8.137	8.600	1.083	1.769
	2.73	2.61	3.93	3.91	0.69	1.21
New Economy	–0.250	–0.244	–0.332	–0.317	0.778	0.877
	–0.45	–0.44	–0.56	–0.53	0.41	0.48
log(Number of Deals)	–0.012	0.012	0.063	0.139	0.234	0.333
	–0.07	0.07	0.36	0.77	0.52	0.77
Adjusted R^2	0.053	0.055	0.040	0.051	0.075	0.135
Number of observations	5,715	5,715	4,827	4,827	888	888
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var.:	0.774	0.774	1.263	1.263	–1.883	–1.883

Table A-5: Size and Bidder Announcement Returns: Regression Results with CEO Overconfidence Proxy

This table presents results for OLS regressions of three-day abnormal bidder announcement returns on bidder size, target size, CEO overconfidence, and control variables for the full sample, only non-public targets, and only public targets. *Longholder Thomson* is the variable *Longholder Thomson fill* from Malmendier, Ulrike, and Geoffrey Tate. 2015. "Behavioral CEOs: The Role of Managerial Overconfidence." Journal of Economic Perspectives, 29 (4): 37-60. We merged the data available at https://www.aeaweb.org/articles?id=10.1257/jep.29.4.37 with our data set for the overlapping sample period from 1997 to 2012. We replaced all missing values of *Longholder Thomson* with zero to prevent a large change in the number of observations in our regressions. We defined *Longholder Missing* to equal one if *Longholder Thomson fill* was missing and zero otherwise. All other variables have previously been defined in Table 2. Bidder MCAP and Dealsize are in logs. The T-statistics are reported in small font size below the estimates. Standard errors are clustered by announcement month.

Dep. var.:	ACAR [−1, +1]					
	All Targets		Non-Public Targets		Public Targets	
	(1)	(2)	(3)	(4)	(5)	(6)
Bidder MCAP	–0.387	–0.897	–0.470	–1.227	–0.065	0.533
	–5.74	–6.30	–6.17	–7.59	–0.51	3.05
Dealvalue		0.790		1.162		–0.953
		4.96		6.43		–4.62
Longholder Thomson	0.371	0.377	0.290	0.275	0.213	0.208
	1.93	1.96	1.39	1.30	0.45	0.44
Longholder Missing	0.206	0.273	0.082	0.152	0.283	0.309
	0.93	1.25	0.37	0.68	0.45	0.50
Public Target	–2.970	–3.976				
	–11.15	–12.77				
Bidder ROA	0.209	0.172	0.203	0.190	6.551	6.605
	0.15	0.13	0.14	0.13	2.30	2.37
Bidder BM Ratio	0.600	0.365	0.600	0.243	0.807	1.034
	1.88	1.12	1.79	0.70	1.15	1.45
Cash	0.139	0.312	–0.100	0.069	2.559	1.810
	0.90	2.11	–0.61	0.44	6.46	4.11
Stock	–0.166	–0.286	0.526	0.348	–0.652	–0.705
	–0.54	–0.93	1.38	0.92	–1.67	–1.78
Tender	1.826	1.964	–2.466	–2.729	1.330	1.193
	4.28	4.51	–1.50	–1.55	2.47	2.21
Hostile	–1.053	–1.990			–1.776	–0.711
	–0.58	–1.03			–0.87	–0.37
Conglomerate	0.062	0.125	0.033	0.109	–0.076	–0.242
	0.27	0.53	0.13	0.41	–0.16	–0.53
Competed	–0.141	–0.615	1.253	0.458	–0.922	–0.465
	–0.18	–0.76	1.06	0.38	–0.92	–0.48
New Economy	–0.641	–0.571	–0.571	–0.471	–1.021	–1.072
	–1.87	–1.63	–1.51	–1.22	–0.96	–1.03
log(Number of Deals)	–0.451	–0.440	–0.318	–0.264	–1.300	–1.098
	–1.68	–1.64	–1.09	–0.90	–1.78	–1.50
Adjusted R^2	0.026	0.035	0.007	0.026	0.090	0.106
Number of observations	13,573	13,573	11,485	11,485	2,088	2,088
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A-6: Size and Bidder Announcement Returns: Regression Results with Time to Completion

This table presents results for OLS regressions of three-day abnormal bidder announcement returns on bidder size, target size, time to completion, and control variables for the full sample, only non-public targets, and only public targets. Time to completion is defined as the number of days between deal announcement and completion (according to SDC). All other variables have previously been defined in Table 2. Bidder MCAP and Dealsize are in logs. The T-statistics are reported in small font size below the estimates. Standard errors are clustered by announcement month.

Dep. var.:	ACAR $[-1, +1]$					
	All Targets		Non-Public Targets		Public Targets	
	(1)	(2)	(3)	(4)	(5)	(6)
Bidder MCAP	–0.485	–0.939	–0.539	–1.194	–0.161	0.318
	–11.86	–11.30	–11.73	–12.86	–2.00	2.63
Dealvalue		0.726		1.047		–0.790
		7.45		9.54		–5.66
Public Target	–2.636	–3.438				
	–11.63	–14.08				
Time to Completion	0.004	0.002	0.004	0.002	0.003	0.004
	5.75	3.90	5.67	3.21	1.99	2.71
Bidder ROA	0.107	0.065	0.305	0.265	1.425	1.416
	0.12	0.07	0.31	0.27	0.61	0.62
Bidder BM Ratio	0.384	0.180	0.436	0.136	0.458	0.643
	2.08	0.97	2.28	0.71	1.01	1.40
Cash	0.198	0.339	–0.035	0.094	1.889	1.340
	1.67	2.98	–0.28	0.78	6.05	4.20
Stock	–0.076	–0.103	0.363	0.343	–0.845	–0.862
	–0.38	–0.52	1.55	1.48	–2.95	–3.01
Tender	1.760	1.782	1.440	1.415	0.893	1.021
	4.26	4.13	1.05	0.94	2.24	2.55
Hostile	0.282	–0.565			0.006	0.959
	0.38	–0.73			0.01	1.15
Conglomerate	–0.086	–0.030	–0.110	–0.050	–0.388	–0.523
	–0.56	–0.19	–0.63	–0.28	–1.24	–1.69
Competed	0.580	0.343	3.925	3.856	–0.949	–0.589
	0.57	0.31	1.65	1.45	–1.54	–0.99
New Economy	–0.608	–0.550	–0.550	–0.475	–0.989	–1.041
	–2.29	–2.06	–1.90	–1.64	–1.35	–1.43
log(Number of Deals)	–0.361	–0.322	–0.218	–0.136	–1.056	–0.958
	–2.71	–2.39	–1.53	–0.94	–3.13	–2.84
Adjusted R^2	0.036	0.044	0.022	0.039	0.078	0.091
Number of observations	23,758	23,758	20,141	20,141	3,617	3,617
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A-7: Size and Bidder Announcement Returns: Regression Results with Analyst Coverage

This table reruns the regression from Table 4, Panel A, specifications (4) and (6), with controls for analyst coverage. *#Analysts (Bidder)* (*#Analysts (Target)*) is the number of analyst firms following the bidder (target) company in the year before the takeover announcement (according to I/B/E/S). All other variables have previously been defined in Table 2. Bidder MCAP and Dealsize are in logs. The T-statistics are reported in small font size below the estimates. Standard errors are clustered by announcement month.

Dep. var.:	ACAR $[-1,+1]$					
	#Analysts		log(#Analysts)		#Analysts missings set to zero	
	Non-Public	Public	Non-Public	Public	Non-Public	Public
	(1)	(2)	(3)	(4)	(5)	(6)
Bidder MCAP	–0.903	0.939	–0.932	1.009	–1.213	0.246
	–8.02	3.84	–8.42	3.93	–12.82	2.00
Dealvalue	0.773	–1.185	0.771	–1.248	1.079	–0.670
	7.31	–4.19	7.29	–4.49	9.74	–4.94
#Analysts (Bidder)	0.005	–0.013	0.115	–0.322	0.010	0.015
	0.31	–0.42	1.10	–0.79	0.92	0.87
#Analysts (Target)		0.025		0.308	–1.180	–0.046
		0.49		0.92	–2.89	–1.37
Bidder ROA	–0.510	5.027	–0.518	5.030	0.224	1.365
	–0.47	1.14	–0.48	1.14	0.23	0.60
Bidder BM Ratio	0.002	1.695	–0.001	1.757	0.132	0.616
	0.01	2.90	0.00	3.02	0.69	1.38
Cash	–0.072	0.698	–0.073	0.699	0.093	1.285
	–0.39	1.09	–0.40	1.10	0.78	4.07
Stock	–0.146	–0.906	–0.147	–0.922	0.391	–0.860
	–0.55	–1.60	–0.55	–1.63	1.68	–3.02
Tender	3.761	1.662	3.746	1.632	1.467	0.863
	1.95	2.36	1.95	2.32	1.02	2.26
Hostile		2.000		2.026		1.057
		1.57		1.61		1.28
Conglomerate	–0.316	–0.721	–0.316	–0.750	–0.065	–0.566
	–1.56	–1.22	–1.56	–1.27	–0.37	–1.86
Competed	4.685	–0.733	4.692	–0.703	3.947	–0.492
	2.55	–0.83	2.56	–0.81	1.48	–0.83
New Economy	–0.383	–1.621	–0.395	–1.633	–0.494	–1.032
	–0.87	–1.28	–0.90	–1.29	–1.70	–1.43
log(Number of Deals)	–0.263	–0.510	–0.264	–0.486	–0.151	–0.862
	–0.95	–0.82	–0.95	–0.78	–1.04	–2.59
Adjusted R^2	0.028	0.119	0.028	0.120	0.039	0.088
Number of observations	8,752	1,219	8,752	1,219	20,231	3,685
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var.:	1.317	–2.438	1.317	–2.438	1.535	–1.395

Table A-8: Size and Bidder Announcement Returns: Regression Results with European Data

This table presents results for OLS regressions of three-day abnormal bidder announcement returns on bidder size, target size, and control variables for the full sample, only non-public targets, and only public targets of European M&A transactions. The initial sample consists of all mergers and acquisitions in the Thomson Reuters SDC database, performed by bidder firms from current EU countries as well as Iceland, Lichtenstein, Norway, and Switzerland announced between January 1, 1980 and December 31, 2017. We use the exact same sample selection criteria as for our main US sample. All deals where the target firm is domiciled outside the aforementioned countries are excluded. Stock market and accounting data is obtained from Datastream. All variables have previously been defined in Table 2. Bidder MCAP and Dealsize are in logs. The T-statistics are reported in small font size below the estimates. Standard errors are clustered by announcement month.

Dep. var.:	ACAR $[-1,+1]$					
	All Targets		Non-Public Targets		Public Targets	
	(1)	(2)	(3)	(4)	(5)	(6)
Bidder MCAP	–0.527	–1.032	–0.565	–1.120	–0.198	–0.224
	–8.13	–9.66	–7.94	–9.58	–1.46	–1.14
Dealvalue		0.784		0.879		0.035
		8.30		8.63		0.16
Public Target	–1.392	–2.144				
	–3.35	–4.67				
Bidder ROA	–0.036	–0.044	–0.037	–0.045	–1.640	–1.626
	–3.68	–4.85	–4.05	–5.24	–1.36	–1.36
Bidder BM Ratio	0.123	0.062	–0.225	–0.280	1.144	1.140
	0.57	0.28	–1.00	–1.19	1.92	1.90
Cash	0.203	0.361	0.092	0.245	1.042	1.056
	1.50	2.69	0.67	1.82	2.17	2.19
Stock	1.372	0.979	1.810	1.381	0.961	0.944
	3.30	2.44	3.13	2.47	1.59	1.56
Tender	0.056	–0.132	1.484	0.999	–0.778	–0.783
	0.13	–0.30	1.28	0.88	–1.56	–1.57
Hostile	–0.459	–1.164			–0.656	–0.685
	–0.48	–1.15			–0.59	–0.61
Conglomerate	0.009	0.058	0.002	0.064	0.169	0.172
	0.05	0.36	0.01	0.38	0.33	0.33
Competed	0.311	–0.044	0.495	0.114	–0.176	–0.190
	0.56	–0.08	0.58	0.13	–0.22	–0.24
New Economy	–0.625	–0.668	–0.582	–0.643	–1.198	–1.194
	–1.69	–1.80	–1.56	–1.72	–0.98	–0.98
log(Number of Deals)	–0.138	–0.094	–0.131	–0.072	–0.223	–0.223
	–1.07	–0.74	–1.00	–0.56	–0.58	–0.58
Adjusted R^2	0.042	0.060	0.042	0.064	0.042	0.041
Number of observations	9,518	9,518	8,511	8,511	1,007	1,007
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean dep. var.:	1.397	1.397	1.552	1.552	0.083	0.083

A.3 M&A Literature Survey

We identify relevant M&A papers by scanning title, abstract, and key words for the following words: merger, M&A, target, acquirer, acquiror, acquisition, takeover, and tender. We only include papers whose central focus is on M&A transactions. Table A-9 summarizes the papers we include in our survey (we provide the full list of papers in Table A-11). Out of 238 papers in total, 84% are mainly empirical. 51% of these empirical papers (102 papers) feature an analysis of bidder announcement returns, and 44% (88 papers) present a regression with short-term bidder announcement returns as a dependent variable. The latter regression, which is about understanding bidder announcement returns, is the focus of our article. The table shows that 94% of papers include at least one size measure as an explanatory variable in this regression.

Based on this sample of papers we conclude that viewing size as a proxy variable for some underlying value driver is pervasive in the literature. By contrast, we have not found a single paper among the papers we survey which would interpret size as a scaling variable but not a proxy variable. For example, a keyword search for "scaling," followed by manual search among the flagged papers does not reveal any relevant hits. It is of course possible that such a paper exists in our sample and we overlooked it. However, even if there was a paper like that in the sample, the conclusion we draw from our literature review is clear: interpreting size as proxy is by far the predominant approach in the recent M&A literature. We present specific examples in Table A-10.

Table A-9: Scan of the M&A Literature

This table summarizes our scan of all M&A papers published from 2000 to 2017 in the *Journal of Finance* (53 papers), the *Journal of Financial Economics* (118), *Management Science* (25), and the *Review of Financial Studies* (42). We identify M&A papers by scanning title and abstract for the following words: merger, M&A, target, acquirer, acquiror, acquisition, takeover, and tender. We only include papers that contain some analysis relating to M&A transactions.

	#papers	% of A	% of B	% of C
All M&A papers [A]	238	100%		
Mostly theory paper	32	13%		
Organizations and business strategy paper	7	3%		
Mostly empirical paper [B]	199	84%	100%	
... with any return regression	125	53%	63%	
... with ACAR regression (all windows)	102	43%	51%	
... with ACAR regression (only short windows) [C]	88	37%	44%	100%
Size controls:				
Bidder size	64			73%
Target size	26			30%
Relative size	62			70%
Only bidder size	9			10%
Only target size	4			5%
Only relative size	8			9%
Bidder and target size	8			9%
Bidder and relative size	40			45%
Target and relative size	7			8%
Bidder, target, and relative size	7			8%
No size controls	5			6%
Additional interactions with size variables	12			14%
Sample:				
Only US acquirer and targets	75			85%
Only private targets	1			1%
Only public targets	36			41%
Public and private targets	51			58%
Sample statistics:	*Mean*	*Median*	*Min*	*Max*
Number of observations	7,759	2,612	64	311,894
Sample start year	1988	1990	1957	2002
Sample end year	2005	2005	1994	2014

Table A-10: Examples of Size as Proxy Explanations

This table lists examples of size-as-proxy explanations found in the M&A literature. The papers we list are merely examples. The papers we list are at a minimum mentioning and taking seriously the size as proxy explanation in the fourth column; the papers are not necessarily finding empirical evidence supporting this explanation. The basis for this table is a survey of all M&A papers published from 2000 to 2017 in the *Journal of Finance* (JF), the *Journal of Financial Economics* (JFE), *Management Science* (MS), and the *Review of Financial Studies* (RFS). We selectively add relevant papers from other journals. In the last two columns, y denotes bidder announcement returns, x denotes the respective size variable, and z denotes the underlying value driver which x proxies for. $\rho(\cdot)$ denotes the correlation coefficient.

Paper	Year	Journal	Size is a proxy for...	Assumed $\rho(x,z)$	Predicted $\rho(y,x)$
Bidder size as proxy:					
Moeller, Schlingemann, and Stulz	2004	JFE	Bidder size is a proxy for managerial hubris	+	−
Moeller, Schlingemann, and Stulz	2004	JFE	Bidder size is a proxy for managerial empire building	+	−
Moeller, Schlingemann, and Stulz	2004	JFE	Bidder size is a proxy for agency problems of free cash flow	+	−
Moeller, Schlingemann, and Stulz	2004	JFE	Bidder size is a proxy for overvaluation	+	−
Moeller, Schlingemann, and Stulz	2004	JFE	Bidder size is a proxy for firm age	+	−
Moeller, Schlingemann, and Stulz	2004	JFE	Bidder size is a proxy for growth opportunities	−	−
Masulis, Wang, and Xie	2007	JF	Bidder size is a proxy for managerial takeover protection	+	−
Netter, Stegemoller, and Wintoki	2011	RFS	Bidder size is a proxy for managerial "machismo"	+	−
Target size as proxy:					
Netter, Stegemoller, and Wintoki	2011	RFS	Target size is a proxy for managerial "machismo"	+	−
Vijh and Yang	2013	JFE	Target size is a proxy for certification of "takeover quality"	−	−
Vijh and Yang	2013	JFE	Target size is a proxy for managerial skill	−	−
Alexandridis, Fuller, Terhaar, and Travlos	2013	JCF	Target size is a proxy for deal complexity	+	−
Relative size as proxy:					
Fuller, Netter, and Stegemoeller	2002	JF	Relative size is a proxy for bargaining power of target firm	+	−
Fuller, Netter, and Stegemoeller	2002	JF	Relative size is a proxy for deal complexity	+	−
Fuller, Netter, and Stegemoeller	2002	JF	Relative size is a proxy for additional monitoring benefits	+	+
Beneish, Jansen, Lewis, and Stuart	2008	JFE	Relative size is a proxy for political influence	+	+

Table A-11: List of Papers from Top 4 Finance Journals used in Literature Review

Authors	Title	Journal	Year
William Schwert	Hostility in Takeovers: In the Eyes of the Beholder?	JF	2000
Sudip Datta, Mai Iskandar-Datta, Kartik Raman	Executive Compensation and Corporate Acquisition Decisions	JF	2001
Vojislav Maksimovic, Gordon Phillips	The Market for Corporate Assets: Who Engages in Mergers and Asset Sales and Are There Efficiency Gains?	JF	2001
Kathleen Fuller, Jeffry Netter, Mike Stegemoller	What Do Returns to Acquiring Firms Tell Us? Evidence from Firms That Make Many Acquisitions	JF	2002
Kee-Hong Bae, Jun-Koo Kang, Jin-Mo Kim	Tunneling or Value Added? Evidence from Mergers by Korean Business Groups	JF	2002
Walter Novaes	Managerial Turnover and Leverage under a Takeover Threat	JF	2002
Benjamin C. Ayers, Craig E. Lefanowicz, John R. Robinson	Shareholder Taxes in Acquisition Premiums: The Effect of Capital Gains Taxation	JF	2003
Ajay Subramanian	Option Pricing on Stocks in Mergers and Acquisitions	JF	2004
Mark Mitchell, Todd Pulvino, Erik Stafford	Price Pressure around Mergers	JF	2004
Matthew Rhodes-Kropf, S. Viswanathan	Market Valuation and Merger Waves	JF	2004
Matthew T. Billett, Tao-Hsien Dolly King, David C. Mauer	Bondholder Wealth Effects in Mergers and Acquisitions: New Evidence from the 1980s and 1990s	JF	2004
Micah S. Officer	Collars and Renegotiation in Mergers and Acquisitions	JF	2004
Omesh Kini, William Kracaw, Shehzad Mian	The Nature of Discipline by Corporate Takeovers	JF	2004
Yakov Amihud, Marcel Kahan, Rangarajan K. Sundaram	The Foundations of Freezeout Laws in Takeovers	JF	2004
Mara Faccio, Ronald W. Masulis	The Choice of Payment Method in European Mergers and Acquisitions	JF	2005
Moeller, Schlingemann, Stulz	Wealth Destruction on a Massive Scale? A Study of Acquiring-Firm Returns in the Recent Merger Wave	JF	2005
Yuanzhi Luo	Do Insiders Learn from Outsiders? Evidence from Mergers and Acquisitions	JF	2005
Dong, Hirshleifer, Richardson, Teoh	Does Investor Misvaluation Drive the Takeover Market?	JF	2006
Audra Boone, Harold Mulherin	How Are Firms Sold?	JF	2007
Bart Lambrecht, Stewart Myers	A Theory of Takeovers and Disinvestment	JF	2007
Hayne Leland	Financial Synergies and the Optimal Scope of the Firm: Implications for Mergers, Spinoffs, and Structured Finance	JF	2007
Jarrad Harford, Kai Li	Decoupling CEO Wealth and Firm Performance: The Case of Acquiring CEOs	JF	2007
Jie Cai, Anand M. Vijh	Effects of Stock and Option Holdings of Target and Acquirer CEOs	JF	2007
Ronald W. Masulis, Cong Wang, Fei Xie	Corporate Governance and Acquirer Returns	JF	2007
Dirk Hackbarth, Erwan Morellec	Stock Returns in Mergers and Acquisitions	JF	2008
Jun-Koo Kang, Jin-Mo Kim	The Geography of Block Acquisitions	JF	2008
Liu Yang	The real determinants of asset sales	JF	2008
Matthew Rhodes-Kropf, David Robinson	The Market for Mergers and the Boundaries of the Firm	JF	2008
Vojislav Maksimovic, Gordon Phillips	The Industry Life Cycle, Acquisitions and Investment: Does Firm Organization Matter?	JF	2008

Authors	Title	Journal	Year
Gary Gorton, Matthias Kahl, Richard Rosen	Eat or Be Eaten: A Theory of Mergers and Firm Size	JF	2009
Harry Huizinga, Johannes Voget	International Taxation and the Direction and Volume of Cross-Border M&As	JF	2009
Pavel Savor, Qi Lu	Do Stock Mergers Create Value for Acquirers?	JF	2009
Ronald W. Masulis, Cong Wang, Fei Xie	Agency Problems at Dual-Class Companies	JF	2009
Andres Almazan, Adolfo de Motta, Sheridan Titman, Vahap Uysal	Financial Structure, Acquisition Opportunities,and Firm Locations	JF	2010
Alex Edmans, Itay Goldstein, Wei Jiang	The Real Effects of Financial Markets:The Impact of Prices on Takeovers	JF	2012
Andrey Golubov, Dimitris Petmezas, Nickolaos G. Travlos	When It Pays to Pay Your Investment Banker: New Evidence on the Role of Financial Advisors in M&As	JF	2012
Isil Erel, Rose Liao, Michael Weisbach	Determinants of Cross-Border Mergers and Acquisitions	JF	2012
Julian Atanassov	Do Hostile Takeovers Stifle Innovation? Evidence from Antitakeover Legislation and Corporate Patenting	JF	2013
Matthew Spiegel, Heather Tookes	Dynamic Competition, Valuation, and Merger Activity	JF	2013
Serdar Dinc, Isil Erel	Economic Nationalism in Mergersand Acquisitions	JF	2013
Vojislav Maksimovic, Gordon Phillips, Liu Yang	Private and Public Merger Waves	JF	2013
Albert Sheen	The Real Product Market Impact of Mergers	JF	2014
Alexander S. Gorbenko, Andrey Malenko	Strategic and Financial Bidders in Takeover Auctions	JF	2014
Claudia Custodio	Mergers and Acquisitions Accounting and the Diversification Discount	JF	2014
Jan Bena, Kai Li	Corporate Innovations and Mergers and Acquisitions	JF	2014
Kenneth Ahern, Denis Sosyura	Who Writes the News? Corporate Press Releases during Merger Negotiations	JF	2014
Kenneth Ahern, Jarrad Harford	The Importance of Industry Links in Merger Waves	JF	2014
Mike Burkart, Denis Gromb, Holger M. Mueller, Fausto Panunzi	Legal Investor Protection and Takeovers	JF	2014
Sandra Betton, Espen Eckbo, Rex Thompson, Karin Thorburn	Merger Negotiations with Stock Market Feedback	JF	2014
Andrew Karolyi, Alvaro Taboada	Regulatory Arbitrage and Cross-Border Bank Acquisitions	JF	2015
Dirk Jenter, Katharina Lewellen	CEO Preferences and Acquisitions	JF	2015
Isil Erel, Yeejin Jang, Michael Weisbach	Do Acquisitions Relieve Target Firms' Financial Constraints?	JF	2015
Asli Arikan, Rene M. Stulz	Corporate Acquisitions, Diversification, and the Firm's Life Cycle	JF	2016
David J. Denis, Timothy A. Kruse	Managerial discipline and corporate restructuring following performance declines	JFE	2000
Moon H. Song, Ralph A. Walkling	Abnormal returns to rivals of acquisition targets: A test of the 'acquisition probability hypothesis'	JFE	2000
P. Raghavendra Rau	Investment bank market share, contingent fee payments, and the performance of acquiring firms	JFE	2000
Stuart L. Gillan, John W. Kensinger, John D. Martin	Value creation and corporate diversification: the case of Sears, Roebuck & Co.	JFE	2000
Gayle L. DeLong	Stockholder gains from focusing versus diversifying bank mergers	JFE	2001

Authors	Title	Journal	Year
Joel F. Houston, Christopher M. James, Michael D. Ryngaert	Where do merger gains come from? Bank mergers from the perspective of insiders and outsiders	JFE	2001
Richard T. Bliss, Richard J. Rosen	CEO compensation and bank mergers	JFE	2001
Timothy R. Burch	Locking out rival bidders: The use of lockup options in corporate mergers	JFE	2001
Andrei Shleifer, Robert W. Vishny	Stock market driven acquisitions	JFE	2002
Malcolm Baker, Serkan Savasoglu	Limited arbitrage in mergers and acquisitions	JFE	2002
Anu Bharadwaj, Anil Shivdasani	Valuation effects of bank financing in acquisitions	JFE	2003
Jarrad Harford	Takeover bids and target directors' incentives: the impact of a bid on directors' wealth and board seats	JFE	2003
Micah S. Officer	Termination fees in mergers and acquisitions	JFE	2003
Thomas W. Bates, Michael L. Lemmon	Breaking up is hard to do? An analysis of termination fee provisions and merger outcomes	JFE	2003
Bart M. Lambrecht	The timing and terms of mergers motivated by economies of scale	JFE	2004
C. Edward Fee, Shawn Thomas	Sources of gains in horizontal mergers: evidence from customer, supplier, andrival firms	JFE	2004
Henock Louis	Earnings management and the market performance of acquiring firms	JFE	2004
Maria Fabiana Penas, Haluk Unal	Gains in bank mergers: Evidence from the bond markets	JFE	2004
Sara B. Moeller, Frederik P. Schlingemann, Rene M. Stulz	Firm size and the gains from acquisitions	JFE	2004
Stefano Rossi, Paolo F. Volpin	Cross-country determinants of mergers and acquisitions	JFE	2004
Thomas J.Chemmanur, An Yan	A theory of corporate spin-offs	JFE	2004
Yaniv Grinstein, Paul Hribar	CEO compensation and incentives: Evidence from M&A bonuses	JFE	2004
Eitan Goldman, Jun Qian	Optimal toeholds in takeover contests	JFE	2005
Erwan Morellec, Alexei Zhdanov	The dynamics of mergers and acquisitions	JFE	2005
Husayn Shahrur	Industry structure and horizontal takeovers: Analysis of wealth effects on rivals, suppliers, and corporate customers	JFE	2005
Jarrad Harford	What drives merger waves?	JFE	2005
Jim Hsieh, Ralph A. Walkling	Determinants and implications of arbitrage holdings in acquisitions	JFE	2005
Jose-Miguel Gaspar, Massimo Massa, Pedro Matos	Shareholder investment horizons and the market for corporate control	JFE	2005
Matthew Rhodes–Kropf, David T. Robinson, S. Viswanathan	Valuation waves and merger activity: The empirical evidence	JFE	2005
Sanjai Bhagat, Ming Dong, David Hirshleifer, Robert Noah	Do tender offers create value? New methods and evidence	JFE	2005
Thomas Moeller	Let's make a deal! How shareholder control impacts merger payoffs	JFE	2005
Joshua D. Rauh	Own company stock in defined contribution pension plans: A takeover defense?	JFE	2006
Matthew J. Higgins, Daniel Rodriguez	The outsourcing of R&D through acquisitions in the pharmaceutical industry	JFE	2006
Mukarram Attari, Suman Banerjee, Thomas H. Noe	Crushed by a rational stampede: Strategic share dumping and shareholder insurrections	JFE	2006
Thomas Hellmann	IPOs, acquisitions, and the use of convertible securities in venture capital	JFE	2006
Thomas W. Bates, Michael L. Lemmon, James S. Linck	Shareholder wealth effects and bid negotiation in freeze-out deals: Are minority shareholders left out in the cold?	JFE	2006

Authors	Title	Journal	Year
Ajay Khorana, Peter Tufano, Lei Wedge	Board structure, mergers, and shareholder wealth: A study of the mutual fund industry	JFE	2007
Malcolm Baker, Joshua Coval, Jeremy C. Stein	Corporate financing decisions when investors take the path of least resistance	JFE	2007
Micah S. Officer	The price of corporate liquidity: Acquisition discounts for unlisted targets	JFE	2007
Xia Chen, Jarrad Harford, Kai Li	Monitoring: Which institutions matter?	JFE	2007
A. Burak Guner, Ulrike Malmendier, Geoffrey Tate	Financial expertise of directors	JFE	2008
Audra L. Boone, J. Harold Mulherin	Do auctions induce a winner's curse? New evidence from the corporate takeover market	JFE	2008
Erwan Morellec, Alexei Zhdanov	Financing and takeovers	JFE	2008
Gregor Matvos, Michael Ostrovsky	Cross-ownership, returns, and voting in mergers	JFE	2008
Leonce L. Bargeron, Frederik P. Schlingemann, Rene M. Stulz, Chad J. Zutter	Why do private acquirers pay so little compared to public acquirers?	JFE	2008
Messod D. Beneish, Ivo Ph. Jansen, Melissa F. Lewis, Nathan V. Stuart	Diversification to mitigate expropriation in the tobacco industry	JFE	2008
Missaka Warusawitharana	Corporate asset purchases and sales: Theory and evidence	JFE	2008
Thomas W. Bates, David A. Becher, Michael L. Lemmon	Board classification and managerial entrenchment: Evidence from the market for corporate control	JFE	2008
Ulrike Malmendier, Geoffrey Tate	Who makes acquisitions? CEO overconfidence and the market's reaction	JFE	2008
Darren J. Kisgen, Jun "QJ" Qian, Weihong Song	Are fairness opinions fair? The case of mergers and acquisitions	JFE	2009
John W. Cooney, Thomas Moeller, Mike Stegemoller	The underpricing of private targets	JFE	2009
Massimo Massa, Lei Zhang	Cosmetic mergers: The effect of style investingon the market for corporate control	JFE	2009
Nihat Aktas, Eric de Bodt, Richard Roll	Negotiations under the threat of an auction	JFE	2009
Robin Greenwood, Michael Schor	Investor activism and takeovers	JFE	2009
Sandra Betton, B. Espen Eckbo, Karin S. Thorburn	Merger negotiations and the toehold puzzle	JFE	2009
David Benson, Rosemarie H. Ziedonis	Corporate venture capital and the returns to acquiring portfolio companies	JFE	2010
Ugur Celikyurt, Merih Sevilir, Anil Shivdasani	Going public to acquire? The acquisition motive in IPOs	JFE	2010
Chen Lin, Micah S. Officer, Hong Zou	Directors' and officers' liability insurance and acquisition outcomes	JFE	2011
Eliezer M.Fich, Jie Cai, Anh L.Tran	Stock option grants to target CEOs during private merger negotiations	JFE	2011
Feng Li, Suraj Srinivasan	Corporate governance when founders are directors	JFE	2011
Heitor Almeida, Murillo Campello, Dirk Hackbarth	Liquidity Mergers	JFE	2011
Heitor Almeida, Sang Yong Park, Marti G. Subrahmanyam, Daniel Wolfenzon	The structure and formation of business groups: Evidence from Korean chaebols	JFE	2011
Jarrad Harford, Dirk Jenter, Kai Li	Institutional cross-holdings and their effect on acquisition decisions	JFE	2011
Jon A. Garfinkel, Kristine Watson Hankins	The role of risk management in mergers and merger waves	JFE	2011
Lucian A. Bebchuk, K. J. Martijn Cremers, Urs C. Peyer	The CEO pay slice	JFE	2011
Olubunmi Faleye, Rani Hoitash, Udi Hoitash	The costs of intense board monitoring	JFE	2011
Quentin Boucly, David Sraer, David Thesmar	Growth LBOs	JFE	2011
Shane Heitzman	Equity grants to target CEOs during deal negotiations	JFE	2011

Authors	Title	Journal	Year
Sugato Bhattacharyya, Amrita Nain	Horizontal acquisitions and buying power: A product market analysis	JFE	2011
Vahap B. Uysal	Deviation from the target capital structure and acquisition choices	JFE	2011
Viral V. Acharya, Yakov Amihud, Lubomir Litov	Creditor rights and corporate risk-taking	JFE	2011
Vojislav Maksimovic, Gordon Phillips, N. R. Prabhala	Post-merger restructuring and the boundaries of the firm	JFE	2011
Jarrad Harford, Mark Humphery-Jenner, Ronan Powell	The sources of value destruction in acquisitions by entrenched managers	JFE	2012
Kenneth R. Ahern	Bargaining power and industry dependence in mergers	JFE	2012
Malcolm Baker, Xin Pan, Jeffrey Wurgler	The effect of reference point prices on mergers and acquisitions	JFE	2012
Ye Cai, Merih Sevilir	Board connections and M&A transactions	JFE	2012
Amrita Nain, Tong Yao	Mutual fund skill and the performance of corporate acquirers	JFE	2013
Anand M.Vijh, Ke Yang	Are small firms less vulnerable to overpriced stock offers?	JFE	2013
Baixiao Liu, John J. McConnell	The role of the media in corporate governance: Do the media influence managers' capital allocation decisions?	JFE	2013
Fangjian Fu, Leming Lin, Micah S. Officer	Acquisitions drivenbystockovervaluation:Aretheygooddeals?	JFE	2013
Hendrik Bessembinder, Feng Zhang	Firm characteristics and long-run stock returns after corporate events	JFE	2013
Jarrad Harford, Robert J. Schonlau	Does the director labor market offer ex post settling-up for CEOs? The case of acquisitions	JFE	2013
Jiekun Huang, Darren J. Kisgen	Gender and corporate finance: Are male executives overconfident relative to female executives?	JFE	2013
Nihat Aktas, Eric de Bodt, Richard Roll	Learning from repetitive acquisitions: Evidence from the time between deals	JFE	2013
Ran Duchin, Breno Schmidt	Riding the merger wave: Uncertainty, reduced monitoring, and bad acquisitions	JFE	2013
Robert Marquez, Rajdeep Singh	The economics of club bidding and value creation	JFE	2013
Soojin Yim	The acquisitiveness of youth: CEO age and acquisition behavior	JFE	2013
Xiaoyang Li	Productivity, restructuring, and the gains from takeover	JFE	2013
Xin Deng, Jun-koo Kang, Buen Sin Low	Corporate social responsibility and stakeholder value maximization: Evidence from mergers	JFE	2013
Jarrad Harford, Vahap B. Uysal	Bond market access and investment	JFE	2014
Joy Ishii, Yuhai Xuan	Acquirer-target social ties and merger outcomes	JFE	2014
Qianqian Huang, Feng Jiang, Erik Lie, Ke Yang	The role of investment banker directors in M&A	JFE	2014
Stacey Jacobsen	The death of the deal: Are withdrawn acquisition deals informative of CEO quality?	JFE	2014
Theodosios Dimopoulos, Stefano Sacchetto	Preemptive bidding,target resistance, and takeover premiums	JFE	2014
Andrey Golubov, Alfred Yawson, Huizhong Zhang	Extraordinary acquirers	JFE	2015
Breno Schmidt	Costs and benefits of friendly boards during mergers and acquisitions	JFE	2015
David Offenberg, Christo Pirinsky	How do acquirers choose between mergers and tender offers?	JFE	2015

Authors	Title	Journal	Year
Eliezer M.Fich, Jarrad Harford, Anh L.Tran	Motivated monitors: The importance of institutional investors' portfolio weights	JFE	2015
Jess Cornaggia, Yifei Maob, Xuan Tian, Brian Wolfe	Does banking competition affect innovation?	JFE	2015
Kenneth R. Ahern, Deniele Daminelli, Cesare Fracassi	Lost in translation? The effect of cultural values on mergers around the world	JFE	2015
Kose John, Anzhela Knyazeva, Diana Knyazeva	Employee rights and acquisitions	JFE	2015
Lee Biggerstaff, David C. Cicero, Andy Puckett	Suspect CEOs, unethical culture, and corporate misbehavior	JFE	2015
Michelle Hanlon, Rebecca Lester,Rodrigo Verdi	The effect of repatriation tax costs on U.S. multinational investment	JFE	2015
Rwan El-Khatib, Kathy Fogel, Tomas Jandik	CEO network centrality and merger performance	JFE	2015
Tao Chen, Jarrad Harford, Chen Lin	Do analysts matter for governance? Evidence from natural experiments	JFE	2015
Vladimir Vladimirov	Financing bidders in takeover contests	JFE	2015
Andriy Bodnaruk, Marco Rossi	Dual ownership, returns, and voting in mergers	JFE	2016
Todd A. Gormley, David A. Matsa	Playing it safe? Managerial preferences, risk, and agency conflicts	JFE	2016
Ulrike Malmendier, Marcus M. Opp, Farzad Saidi	Target revaluation after failed takeover attempts: Cash versus stock	JFE	2016
Anton Babkin, Brent Glover, Oliver Levine	Are corporate inversions good for shareholders?	JFE	2017
Cornelius Schmidt, Rüdiger Fahlenbrach	Do exogenous changes in passive institutional ownership affect corporate governance and firm value?	JFE	2017
Doron Levit	Advising shareholders in takeovers	JFE	2017
Laura Casares Field, Anahit Mkrtchyan	The effect of director experience on acquisition performance	JFE	2017
Matthew D. Cain, Stephen B. McKeon, Steven Davidoff Solomon	Do takeover laws matter? Evidence from five decades of hostile takeovers	JFE	2017
Nicole M. Boyson, Nickolay Gantchev, Anil Shivdasani	Activism mergers	JFE	2017
Oliver Levine	Acquiring growth	JFE	2017
Olivier Dessaint, Andrey Golubov, Paolo Volpin	Employment protection and takeovers	JFE	2017
Theodosios Dimopoulos, Stefano Sacchetto	Merger activity in industry equilibrium	JFE	2017
Diwakar Gupta, Yigal Gerchak	Quantifying Operational Synergies in a Merger/Acquisition	MS	2002
Richard M. Cyert, Sok-Hyon Kang, Praveen Kumar	Corporate Governance, Takeovers, and Top-Management Compensation: Theory and Evidence	MS	2002
Roberto A. Weber, Colin F. Camerer	Cultural Conflict and Merger Failure: An Experimental Approach	MS	2003
Claude Montmarquette, Jean-Louis Rullière, Marie-Claire Villeval, Romain Zeiliger	Redesigning Teams and Incentives in a Merger: An Experiment with Managers and Students	MS	2004
Matthew T. Billett, Yiming Qian	Are Overconfident CEOs Born or Made? Evidence of Self-Attribution Bias from Frequent Acquirers	MS	2008
Samina Karim	Business Unit Reorganization and Innovation in New Product Markets	MS	2009
Xinlei Zhao	Technological Innovation and Acquisitions	MS	2009
Eric Van den Steen	Culture Clash: The Costs and Benefits of Homogeneity	MS	2010
Maurice Levi, Kai Li, Feng Zhang	Deal or No Deal: Hormones and the Mergers and Acquisitions Game	MS	2010

Authors	Title	Journal	Year
Sam Ransbotham, Sabyasachi Mitra	Target Age and the Acquisition of Innovation in High-Technology Industries	MS	2010
Jaideep Shenoy	An Examination of the Efficiency, Foreclosure, and Collusion Rationales for Vertical Takeovers	MS	2012
Santiago Mingo	The Impact of Acquisitions on the Performance of Existing Organizational Units in the Acquiring Firm: The Case of an Agribusiness Company	MS	2013
Hassan Tehranian, Mengxing Zhao, Julie L. Zhu	Can Analysts Analyze Mergers?	MS	2014
Henri Servaes, Ane Tamayo	How Do Industry Peers Respond to Control Threats?	MS	2014
Carol Marquardt, Emanuel Zur	The Role of Accounting Quality in the M&A Market	MS	2015
David A. Becher, Jonathan B. Cohn, Jennifer L. Juergens	Do Stock Analysts Influence Merger Completion? An Examination of Postmerger Announcement Recommendations	MS	2015
Ling Cen, Sudipto Dasgupta, Rik Sen	Discipline or Disruption? Stakeholder Relationships and the Effect of Takeover Threat	MS	2016
Oktay Akkus, J. Anthony Cookson, Ali Hortaçsu	The Determinants of Bank Mergers: A Revealed Preference Analysis	MS	2016
Anjana Rajamani, Marieke van der Poel, Abe de Jong, Steven Ongena	The International Diversification of Banks and the Value of Their Cross-Border M&A Advice	MS	2017
Dan Bernhardt, Tingjun Liu, Robert Marquez	Targeting Target Shareholders	MS	2017
Eric de Bodt, Jean-Gabriel Cousin, Richard Roll	Full-Stock-Payment Marginalization in Merger and Acquisition Transactions	MS	2017
Exequiel Hernandez, Anoop Menon	Acquisitions, Node Collapse, and Network Revolution	MS	2017
Jun Qian, Julie Lei Zhu	Return to Invested Capital and the Performance of Mergers and Acquisitions	MS	2017
Justin Frake	Selling Out: The Inauthenticity Discount in the Craft Beer Industry	MS	2017
Xiumin Martin, Ron Shalev	Target Firm-Specific Information and Acquisition Efficiency	MS	2017
Sandra Betton, B. Espen Eckbo	Toeholds, Bid Jumps, and Expected Payoffs in Takeovers	RFS	2000
Francesca Cornelli, David D. Li	Risk Arbitrage in Takeover	RFS	2002
Jay C. Hartzell, Eli Ofek, David Yermack	What's In It for Me? CEOs Whose Firms Are Acquired	RFS	2004
Mary M. Bange; Michael A. Mazzeo	Board Composition, Board Effectiveness, and the Observed Form of Takeover Bids	RFS	2004
Ann B. Gillette, Thomas H. Noe	If at First You Don't Succeed: The Effect of the Option to Resolicit on Corporate Takeovers	RFS	2006
Paul Povel, Rajdeep Singh	Takeover Contests with Asymmetric Bidders	RFS	2006
Audra L. Boone, J. Harold Mulherin	Do Termination Provisions Truncate the Takeover Bidding Process?	RFS	2007
Moeller, Schlingemann, Stulz	How Do Diversity of Opinion and Information Asymmetry Affect Acquirer Returns?	RFS	2007
Arturo Bris, Christos Cabolis	The Value of Investor Protection: Firm Evidence from Cross-Border Mergers	RFS	2008
Christa H. S. Bouwman, Kathleen Fuller, Amrita S. Nain	Market Valuation and Acquisition Quality: Empirical Evidence	RFS	2009
Cong Wang, Fei Xie	Corporate Governance Transfer and Synergistic Gains from Mergers and Acquisitions	RFS	2009
Erik Devos, Palani-Rajan Kadapakkam, Srinivasan Krishnamurthy	How Do Mergers Create Value? A Comparison of Taxes, Market Power, and Efficiency Improvements as Explanations for Synergies	RFS	2009

Authors	Title	Journal	Year
K. J. Martijn Cremers, Vinay B. Nair, Kose John	Takeovers and the Cross-Section of Returns	RFS	2009
Anand M. Goel, Anjan V. Thakor	Do Envious CEOs Cause Merger Waves?	RFS	2010
Anusha Chari, Paige P. Ouimet, Linda L. Tesar	The Value of Control in Emerging Markets	RFS	2010
Gerard Hoberg, Gordon Phillips	Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis	RFS	2010
Miguel A. Ferreira, Massimo Massa, Pedro Matos	Shareholders at the Gate? Institutional Investors and Cross-Border Mergers and Acquisitions	RFS	2010
Richard A. Brealey, Ian A. Cooper, Evi Kaplanis	Excess Comovement in International Equity Markets: Evidence from Cross-border Mergers	RFS	2010
Ulrich Hege, Christopher Hennessy	Acquisition Values and Optimal Financial (In)Flexibility	RFS	2010
David Haushalter, Michelle Lowry	When Do Banks Listen to Their Analysts? Evidence from Mergers and Acquisitions	RFS	2011
Hans Degryse, Nancy Masschelein, Janet Mitchell	Staying, Dropping, or Switching: The Impacts of Bank Mergers on Small Firms	RFS	2011
Isil Erel	The Effect of Bank Mergers on Loan Prices: Evidence from the United States	RFS	2011
Jack Bao, Alex Edmans	Do Investment Banks Matter for M&A Returns?	RFS	2011
Jeffry Netter, Mike Stegemoller, M. Babajide Wintoki	Implications of Data Screens on Merger and Acquisition Analysis: A Large Sample Study of Mergers and Acquisitions from 1992 to 2009	RFS	2011
Jie Cai, Moon H. Song, Ralph A. Walkling	Anticipation, Acquisitions, and Bidder Returns: Industry Shocks and the Transfer of Information across Rivals	RFS	2011
Kristina Minnick, Haluk Unal, Liu Yang	Pay for Performance? CEO Compensation and Acquirer Returns in BHCs	RFS	2011
Paolo Fulghieri, Merih Sevilir	Mergers, Spinoffs, and Employee Incentives	RFS	2011
Sris Chatterjee, Kose John, An Yan	Takeovers and Divergence of Investor Opinion	RFS	2012
Tingjun Liu	Takeover Bidding with Signaling Incentives	RFS	2012
Cláudia Custódio, Daniel Metzger	How Do CEOs Matter? The Effect of Industry Expertise on Acquisition Returns	RFS	2013
Gordon M. Phillips, Alexei Zhdanov	R&D and the Incentives from Merger and Acquisition Activity	RFS	2013
Kathryn Barraclough, David T. Robinson, Tom Smith, Robert E. Whaley	Using Option Prices to Infer Overpayments and Synergies in M&A Transactions	RFS	2013
Paige Parker Ouimet	What Motivates Minority Acquisitions? The Trade-Offs between a Partial Equity Stake and Complete Integration	RFS	2013
Peter Roosenboom, Frederik P. Schlingemann, Manuel Vasconcelos	Does Stock Liquidity Affect Incentives to Monitor? Evidence from Corporate Takeovers	RFS	2014
Valeriy Sibilkov, John J. McConnell	Prior Client Performance and the Choice of Investment Bank Advisors in Corporate Acquisitions	RFS	2014
Suman Banerjee, Mark Humphery-Jenner, Vikram Nanda	Restraining Overconfident CEOs through Improved Governance: Evidence from the Sarbanes-Oxley Act	RFS	2015
Ugur Lel, Darius P. Miller	Does Takeover Activity Cause Managerial Discipline? Evidence from International M&A Laws	RFS	2015
Marco Becht, Andrea Polo, Stefano Rossi	Does Mandatory Shareholder Voting Prevent Bad Acquisitions?	RFS	2016

Authors	Title	Journal	Year
Vineet Bhagwat, Robert Dam, Jarrad Harford	The Real Effects of Uncertainty on Merger Activity	RFS	2016
Elisabeth Kempf, Alberto Manconi, Oliver Spalt	Distracted Shareholders and Corporate Actions	RFS	2017
Jonathan M. Karpoff, Robert J. Schonlau, Eric W. Wehrly	Do Takeover Defense Indices Measure Takeover Deterrence?	RFS	2017
Laurent Frésard, Ulrich Hege, Gordon Phillips	Extending Industry Specialization through Cross-Border Acquisitions	RFS	2017